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# A NEW GENERAL MECHANISTIC MODEL FOR PREDICTING CIVIL DISTURBANCES AND THEIR CHARACTERISTICS



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# Abstract

Since the wave of civil violence in the USA in the 1960s, many social theorists have tried to explain why riots occur. Despite at least 50 years of research since then, there is still not enough insight to anticipate large events like the 2011 Arab Spring and London riots. The main goal of this thesis is therefore to improve understanding about how underlying conditions influence and drive riot dynamics, such as the intensity, spread, and duration.

I develop a new mechanistic and stochastic agent-based model for riots. Previous models have either only targeted general phenomena associated with riots, or aimed at behaviour specific to a single event. In this thesis I combine both approaches: I demonstrate how the model in which the motivation of the agents is based on general concepts, can be applied to the specific situation of the 2011 London riots. The model reproduces the majority of the behaviour observed in the London riots ( $\rho = 0.4-0.8$ ).

One of the key factors under investigation is the relationship between protests and outbursts of civil violence. Riots are often preceded by protests, such that a large pool of potential rioters is directly available. I find that the number of times a protest is repeated has greater influence on riot dynamics than the protest crowd size. The support shown during demonstrations might incite false confidence in individuals, potentially leading to quicker escalation.

Another question is how contact networks and collective identity influence the spread of violence between different locations. The role of online social media (e.g. Twitter) has been a major focus in trying to explain why the violence in the 2011 Arab spring spread so quickly and so far. I investigate the role of social similarity as another factor that might have contributed to the diffusion of unrest, and demonstrate the existence of a critical transition in riot activity when increasing the density of the contact network in the model. Such increases in density beyond the critical thresholds might have been introduced by online social networks.

Finally, I explore the sensitivity to cooperation of different potential riot groups. In some cases, mixed populations with different collective identities can form coalitions within neighbourhoods based on shared grievances, which could lead to increases in riot size and riot probability. I examine the influence of the social structure and spread of these populations over different neighbourhoods, as well as the overlap in grievances and different demographic structures.





# Lay Summary

Since the wave of violence from the ‘race riots’ in the 1960s in the USA many researchers from the social disciplines (e.g. sociology, political theory, economy, psychology) have tried to understand under which conditions riots and civil violence occurs. Despite at least 50 years worth of research since then, some riots still come as a surprise. Understanding how underlying conditions give rise to these events is important, as it can help address these in advance and prevent the escalation of violence.

In this work I take another approach, by using mathematical formulae and computer simulations (numerical modelling) to describe riots. Such methods are different than the statistical analyses that are now commonplace in social theory. Statistical analyses give indications on how strongly things relate to each other, but do not give information on what the exact relationships are and why they exist. In mechanistic numerical models the relationships between variables are explicitly declared, such that scientists are able to explore what would have happened if the surrounding circumstances of an event would have been different. These methods are also used to predict and understand for example, the weather, climate change, and traffic density.

In this thesis I use a specific method called agent-based modelling, where the human behaviour is implemented into so-called agents, which are simplified representations of individuals. Much like self driving cars, some aspects of human behaviour can be captured in algorithms, where the behaviour is generalised to simple rules. In traffic this means stopping for a red light, and going on green. In my model the decision for an agent to join a riot is based on strength of the strife an agent experiences, the risk of joining the riot (i.e. how many police officers are responding), and the friends an agent has that are currently participating in the riot.

This thesis is divided into three research chapters, each with its own specific research question. In the first chapter I explore the relationship between protests and riots. The second chapter looks at under which conditions violence spreads from one location to another, such as in the Arab spring where unrest started in Tunisia, but eventually spread to many other countries in Northern Africa and the Middle-East. The last research chapter looks at when different populations in cities might riot together because of shared socio-economic conditions.



# Author's Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own.

Jelte P. Mense

1-10-2017



# Acknowledgments

First I would like to thank my supervisors Paul Palmer and Matthew Smith, without them I could have never started and completed this project. They designed the original research question and the project, and gave me the opportunity to create this thesis from the original project description. I thank them in particular for their neverending interest in the project, frequent meetings, swift delivery of feedback, and guidance throughout the past four years. Also I am very grateful for all my family and friends who have supported me throughout my studies, offering advice and friendship, and also provided the sometimes highly necessary escape and distraction.

I thank Microsoft Research Cambridge for funding the project, and moreover for hosting me multiple times and allowing me to do an internship at their offices. I also thank the London Metropolitan Police Service and the Stockholm Police for giving me the data on the 2011 London and 2013 Stockholm riots, which offered great insights into how to set up the model and which behavioural dynamics to target.

Lastly I would like to thank those who have taught me the necessary methods and knowledge that allowed me to conduct the experiments in this thesis. The interdisciplinarity of my work has made me increasingly aware of how foundational the Roosevelt Academy, now called University College Roosevelt, has been in enabling me to combine science and social theory. Without the enthusiastic teachers, in particular the belief and support of Dr. Richard van den Doel and Prof.Dr. Henk Meijer, I would likely never have aspired to obtaining a PhD.



# Ethics Statement

In this thesis I present a new mechanistic agent-based model for describing the evolution and dynamics of riots. I apply the model in the context of the London riots, and explore alternative scenarios to find the influence of pre-riot protests, police response, and information accuracy. Additionally I use the model to investigate the impact of social networks, similarities and dissimilarities in social identities between groups, and correlation between potential riot causes on the spread of violence from one location to another. I also find the effects of demographic shifts and the spatial distribution of (different) potential riot participants within a network on riot duration and activity in the model.

The drive behind this thesis is to establish a new model for describing riots. One of the broader original aims of this research was to find out how climate change could potentially induce conflict. One pathway for conflict is that climate change can induce shortage of essential resources, e.g. food and water, possibly leading to unrest. To enable research that investigates how likely these effects are and when and where they could occur, I developed the model presented in this thesis. The concepts that motivate the agents to join the riot in the model are general in nature, and where possible are based on contributions from social theory. Due to the general nature of the model, it could theoretically be applied to multiple specific riot situations. As a demonstration of how the model can be used to describe a specific event I apply the model to the London 2011 riots.

In this thesis I explore and compare several events of civil unrest, including protests, riots, and revolutions. This work is not about the legitimacy or illegitimacy of these events, or other related aspects such as social movements, the use and targets of violence, the initiators and participants of civil unrest, and the resulting police response. The goal is not to predict individual riots, but to understand the contexts in which these events emerge and develop, particularly how the initial and underlying conditions can help explain how unrest evolves after it has started. Through a model that can uncover this information I can contribute to understanding why certain events unfolded the way they did, and why their phenomenology differs from other events.



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This research does not involve experiments involving real human subjects, and does not contain data pertaining to specific identifiable individuals aside from publicly known figures and the names of academic authors. There are two potential issues with this work. The first is that (parts of) the results and conclusions of this thesis could be republished elsewhere in the wrong context, and consequently could be misinterpreted. In the last research chapter for example I investigate the influence of the age structure of a population on riot activity, in the context of immigration. There are repeated disclaimers and explanations throughout the research chapter that point out that 1) the underlying methodology is much more general and not specific to immigration, and 2) I only explore two potentially negative effects of immigration, and that there are other (positive) factors and influences that are not covered in the experiments. Ignoring this information and selecting only certain parts of the analysis might result in the impression that my work is making a (political) statement against immigration, rather than trying to understand the context in which unrest can potentially occur.

The second issue is that my model, and possibly also the results of my research, can be abused to secure or destabilise leadership or influence. Alternatively my model can be used as the basis of another model that would allow such (mis)applications. As I assume that a riot always occurs in the model, I use it to investigate different scenarios rather than predict the next episode of civil violence. Through the simulation of multiple scenarios, I explain why and how some factors contribute to the maximum and minimum riot activity. Potentially such information could be used in the real world to minimise the possibility for (violent) opposition and strengthen the position of those in power. Conversely these findings could be similarly exploited in an attempt to cause maximum unrest and destabilise existing power structures. The model in its current form is limited in the degree to which it can be employed to describe specific locations, as I only incorporate the age distribution of the area and population under investigation. The model therefore needs to be considerably expanded before it can be used with confidence in the manners outlined previously.

The problem of abuse of scientific tools is a wider issue that also applies to other academics and organisations that build models of (civil) conflict. The underlying questions are how 'real' models of social systems should become, and what potential other applications there are beyond the pursuit of the original research questions. Throughout this thesis I mention that models like these can potentially be used by the police to anticipate and mitigate risks, and consequently prevent or limit the

escalation of violence. This is in context of events like the London 2011 and Stockholm 2013 riots, where the spread and escalation of violence resulted in large damages to both private and public properties, including shops, cars, and schools, that had no connection to the original issue of the riot. However, these potential applications are and remain purely theoretical with regards to my model. Besides requests for data to the Stockholm and London police, there has been no contact between me and any other third party, including police and governmental personnel or other groups and organisations, about applying this work in the real world.



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# CHAPTER 1

## Introduction

### ABSTRACT

Since the ‘race riots’ in the 1960s many researchers have tried to understand under which conditions such events occur. The majority of contributions thus far have relied on social theory, but despite 50 years of research outbreaks of civil violence can still come as a surprise. Numerical models have been used to predict a wide range of phenomena, such as the daily weather, global warming and climate change, and traffic density. In this thesis I introduce a new mechanistic agent-based model that can be used to gain a more systemic understanding of riots and to describe different riot scenarios. Apart from understanding if and when violence could occur, it is also useful to know how underlying conditions influence the subsequent evolution of an event after it has started. This leads to the question that is addressed in this thesis, what factors drive riot dynamics, such as duration, intensity, and diffusion.

**Author Contributions:** This chapter was written by Jelte Mense, with editorial contributions from Paul Palmer and Matthew Smith.

# 1.1 Introduction

When multiple individuals share a common grief or disagreement, they can come together and form a crowd, demonstrating their dissent. Sometimes these groups also opt to use violence, for example against police officers. In more extreme cases civil violence can be accompanied by looting and arson, such as in the 2011 London riots and the 2013 Stockholm riots [161, 170]. These forms of civil unrest can lead to severe economic damages to both private and public properties, and tear the social fabric by polarising communities in society. Being able to understand in what contexts these violent events occur is important to prevent and address those circumstances, and if necessary anticipate and mitigate risks associated with the escalation of civil violence.

Uprisings and revolutions have first been captured and studied by the disciplines of the arts and humanities, e.g. through (analyses of) paintings, songs, and history (e.g. [209]). After multiple riots in the 1960s in the USA civil disturbances gained more attention of social theorists (e.g. [2, 178, 180, 196]). Despite at least 50 years of research since those events [215], riots still occur in the USA and in other parts of the world. On the European continent for example in the last decade of 2005 to 2015 there have been large riots in Paris in 2005 [171], London in 2011 [161], Stockholm in 2013 [170], and a revolution in Ukraine in 2014 [99]. Other major events of social conflict in Asia and Africa are the Istanbul riots in 2013 [203] and the earlier Arab spring in 2011 [22, 35], which included protests, riots, revolutions, and civil war in multiple countries across North-Africa and the Middle-East.

New technology has led to the widespread adoption of smartphones and the rise of online social media. Online social networks like Facebook and Twitter are much denser than their offline counterparts [107], and thus allow for a faster dissemination of information between individuals. Additionally the rate and frequency at which information can be shared has grown, for example by broadcasting messages to all contacts with the single press of a button, or leaving a message on a central community page or ‘wall’ within a social network. Through these online social media networks individuals have gained more opportunity to self-organise in gatherings and crowds, facilitating highly coordinated collective actions [183].

The role of social media has been a major focus in investigating both the London riots and the Arab spring in 2011 [22, 80]. During both events there was general surprise over the rate at which violence spread from one location to another, believed

to be driven by the use of online social media. The unprecedented speeds by which information can be shared by the general population leads to questions of whether such events are now more likely to occur, and what the best responses are to crowds that can more rapidly self-organise and coordinate.

Technological advances in computing have also allowed scientists to gather and process more data, and to create more complex models by using numerical simulation. Numerical (computer) simulation allows for the study of complex quantitative models that cannot be solved analytically, and moreover has enabled a stronger focus on stochastic processes. For example large scale simulation of processes in the atmosphere have enabled prediction about the weather and the climate-earth system. Numerical simulations can also be used to describe human behaviour, acting as a substitute for real life experiments [48, 87]. By numerically describing human interactions in a quantitative model scientists can explore a wide range of scenarios and gain a more systemic understanding of societal processes by treating the model as the experiment. This is particularly useful in events like riots and revolutions, which are happen relatively infrequently [48]. In this thesis I propose a numerical model to study riots in context of social effects and interaction, such as demographic population structure and social networks, immigration and segregation, and protests.

This chapter first examines some of the different types of events that fall under the broad category of civil disturbances, such as protests, riots, and revolutions Then I summarise the key past contributions from social theories to research into collective actions such as riots. The contributions that are discussed can be split into two separate categories: 1) those that use a rational framework for explaining the decisions of individuals to engage in collective action, and 2) those that focus on the perceptions, experiences, emotions, and cognitive states of individuals to explain the motivations to join various forms of civil conflict. The following section discusses previous attempts to build numerical models of several forms of civil conflict. This is followed by studies of social media and networks, given the recent relevance of online social networks like Facebook and Twitter. The last sections present the specific research questions addressed in this thesis, and outline the content chapters that follow.



# 1.2 From Protests to Revolutions

Protests or demonstrations, riots, rebellions, and revolutions describe various degrees of activity against a government, but are often used interchangeably or generalised to the same activity [114, 115, 129]. Likewise terms such as civil unrest, disorder, disobedience, disturbances and civil violence are also used interchangeably to describe a wide range of situations. Sometimes simplifying these different forms of activity is done on purpose, for example to build a unified model of collective violence [115], but in other cases theories and models of protests and riots are wrongly applied to revolutions [129], or revolutions are diminished to protests [35]. The use of these terms is further complicated outside the academic literature, where different newspapers that inform the public might describe the same event differently, e.g. a violent protest instead of a riot. This section discusses some of the previous ways in which these different events have been defined, and presents the definitions that I use for the rest of this thesis.

One way to differentiate between different forms of civil unrest has been to consider the legality. Events could therefore fall into two categories, those that were legitimate and were within the law, and illegitimate ones that violated the law. Social psychologists then argued that different motivations could be involved in joining such acts of collective action [92, 184].

A more important distinction is whether such events are tolerated and how they are responded to by the police, rather than their legal legitimacy. For example, protest marches sometimes are arranged very shortly after an incident, such as in the case of the London 2011 riots [161]. Due to the short timeframe it is unlikely that all such demonstrations have the appropriate permits or permission. Rather than responding with repression, governments have the option to tolerate such technically illegitimate protests instead, providing a police force only to contain any possible (violent) altercations. The difference for the individuals who consider participation is then that their efforts are not explicitly repressed by the police, as if the protest were legal.

Additionally there are large discrepancies between the legal and academic definitions of riots [215]. Different countries define riots as an unlawful assembly of people gathering to disturb the peace, where the minimum number of participants depends on the country and varies from a group size of three to twelve. Generally the

academic definition describes a far greater group size, varying from a minimum group size between 30 to 50, or even more. Of the riots in the 1960s, virtually all involved at least 50 or more participants [143]. In smaller gatherings individuals who participate might not consider their assembly to be a riot because their group size is insufficiently large, whereas they can be treated as such by the responding police officers, which might escalate into further conflict.

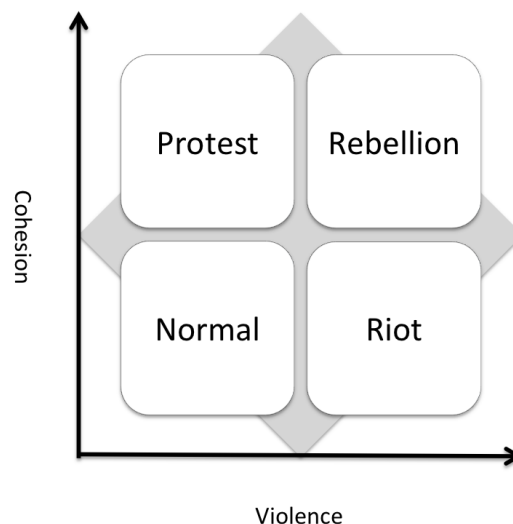
Events such as riots, rebellions and revolutions are typically characterised by the use of violence [143], which is generally perceived by the state as illegitimate and illegal. Another way then to characterise events is the use and targets of aggression and violence [115, 120]. For example the destruction of private property is larger in riots, whereas rebellions and revolutions particularly target state property and personnel. This also leads to a key distinction between revolutions and other forms of civil unrest. Revolutions and rebellions are orientated and coordinated collective attack movements aimed specifically to neutralise and replace those in power [117]. Protesters and rioters generally demand change of some sort, which can include a change of government or individual in power, but do not attack those in charge directly.

Acts of civil unrest against the government can therefore be divided into three different categories. Protests in this work refer to gatherings that are aimed to be a non-violent expression of frustration or a demand for change. Riots refer specifically to those situations that include violence against police forces and both private and public property surrounding the event. The last category consists of rebellions and revolutions, where violence is coordinated against specific state targets, aimed at crippling, stopping, and replacing the operation of a government. A possible fourth category consists of violence specifically against other civilians, such as in the case of ethnic cleansing [33]. However, as this work mainly focuses on riots such acts of collective action are outside the scope of this work.

A second dimension which can be used to differentiate between protests, riots and revolutions is by considering the level of cohesion and coordination between individuals (see Figure 1.1). In a normal situation there is little cohesion between individuals: everyone goes their own way and there is no violence [115, 120]. In a demonstration individuals gather to express a common opinion or demand, e.g. the end of excessive use of violence by police forces against minorities. In the rest of this thesis I assume that events of protests and demonstrations are (initially) intended to be peaceful, and are not expected to result in violence.

## 1.2 From Protests to Revolutions

The level of coordination in riots is less than in protests, as they are mostly not very well-defined by a common goal or specific claim [115, 143]. Moreover the targets of aggression in such situations are mostly defined by the location and opportunities in which these events take place. The drop in cohesion becomes apparent when protests transform into riots; a protest march for example breaks up into smaller groups, that undertake uncoordinated and opportunistic attacks on responding police officers. The level of coordination between individuals increases when the situation transforms from a riot to a revolution. Rather than burning cars, assaulting police officers, and looting, the behaviour shifts towards targeted attacks on government property and personnel. The common goal and targets results in a shared ideology between participants that allows for a higher level of coordination.



**Figure 1.1: Four stages of civil unrest.** *In the normal situation there is no violence, and the (ideological) cohesion between individuals is low. In protests there is similarly little violence, but those that are in the demonstration share a common belief that something should change. In a riot the violence increases, but the targets of the violence are situational and organisation is low. In rebellions and coups, the violence is high like in riots, but is aimed at very specific targets with the goal to cripple and disable the government.*

A clear distinction between protests, riots, and revolutions is not always possible. For example some protests are initially peaceful, but can spiral out of control and result in violent clashes between participants and police. A good example is the recent revolution in Ukraine in 2014. After the government opted to choose a treaty with the Russian Federation over the European Union, the Ukrainian population in Kiev

initially started protesting this decision on the Maidan Square [185]. Fuelled by MEPs Guy Verhofstadt and Hans van Baalen [208], the protest grew and escalated, becoming a violent riot [99]. The crowds later started coordinating their attacks toward specific government buildings in Kiev and became a riot-revolution, eventually leading to president Viktor Yanukovich fleeing to the Russian Federation and new elections [185].

There have also been attempts to classify and categorise different events of rioting, or to build an index of severity for such events [210]. Some of the proposed metrics are simple, like the duration, crowd size, and number of arrests [180] that can objectively be measured, whereas others are more qualitative, e.g. the presence of a goal or a generalised belief, the instrumentality of violence, whether or not there is an intent to overthrow a government, and the passivity of a crowd [117]. But despite all these aspects in which riots can differ from each other, there are also many things that are shared between events. In Section 1.8, I propose a general riot pattern shared by many modern events that I use as a target for my model simulations. The next sections first introduce different theories and methods to find and describe the motivation of individuals to join in events of collective action, including protests, riots, and rebellions.

# 1.3 Rational Choice and Collective Action

Riots, revolutions, and protests are forms of collective action, in which individuals come together and interact, forming gatherings and crowds, working together towards a (perceived or imagined) common goal. Early studies of collective action have attempted to explain under which conditions individuals would work together to provide or create a 'public good' (e.g. [142]). In these studies the outcome of collective action is the provision of a public good, for example a neighbourhood cleanup, improved air quality, national defense, public benches, flood protection, and neighbourhood patrols. To determine under which conditions individuals gather to provide a public good, the motivation of so-called 'actors' (individuals) for movement participation is described as a combination of potential (monetary) benefits and costs. In the simplest case the total profit equals the value of the public good, which is then divided amongst all those who would benefit from the provision of that public good to define the individual gain. Associated with the provision of the public good is also a total cost or investment, which is equally shared among those who participate [71, 118, 142].

The studies that investigate collective action mainly examine the provision of public goods. Associated with such goods are benefits or profits provided by the collective action, and costs or investments through participation in the action. A key characteristic for public goods is that anyone can enjoy them freely, without having to contribute towards the production of that good. In other words, public goods are non-exclusive, and the benefits or profits of such goods can be shared by anyone. Contrasting to these public goods are private or exclusive goods, where only those who participate or share the investment costs have access to the resulting benefits.

The conditions under which people participate in collective action are explored through a framework of economics and rational choice theory. Individuals are represented by actors, and the assumptions are made that these actors who are considering to participate are primarily self-interested and are (fully) rational [142]. Under these assumptions the actors only participate in the provision of the public good if the resulting benefits outweigh the contribution costs.

The combination of rational self-interested actors and the provision of public goods through collective actions leads to the free-rider problem, which is central to the study of collective action [142]. As anyone can access the profits of a public

good provided by a collective action, there is an incentive to free-ride on the efforts of those who participate and have to bear the investment costs. For example in a neighbourhood cleanup all those who live in the area benefit from cleaned streets and pavements, but the time and effort invested in the cleaning is only shared among the group of inhabitants who actually pick up the brooms.

The actors involved in the collective action and the provision of the public good are rational and self-interested. They therefore calculate the benefit and costs individual to them, resulting in an individual net profit. As the number of actors that have access to a certain public good and the value of that good are constant, the individual net profit is dependent on the number of actors that participate in the provision of that good. Participation should be encouraged, as more participants lead to smaller individual time investments, and higher individual net profits. If actors choose to free-ride instead, the individual investment for the others increases. This lowers the efficacy of the collective action, leading to potential failure of the provision of the public good. For these reasons much of the literature of rational choice theory and collective action is devoted to finding the contexts in which the free-rider problem can be overcome and active participation is stimulated such that everyone is mobilised and engaged in the provision of a collective good (e.g. [71, 118, 139, 142]).

The free-rider problem applies particularly to protests and demonstrations for or against some form of political change or measures. Usually such acts of collective action do not involve all those who would benefit from whatever the demonstration is about, but instead consists of a select subgroup acting on behalf of a larger group. For these groups participation is crucial, as one of the ways of measuring the popularity of claims is the number of individuals involved. The success and benefits for this group in these situations thus depends on the ability to mobilise members of the group to engage in a demonstration. Particularly important is to obtain a so-called *critical mass*, a certain population size of participants beyond which others will join too, as explained in the next section.

# 1.4 The Theory of Critical Mass

One of the key aspects of the models that use a formal theory of collective action and rational choice, as described in the previous section, is the homogeneity of the described individuals. Although the homogeneity of actors is not explicitly stated in these models, the behaviour of the group is often extrapolated from analysing the actions of a single actor, thus implicitly assuming some form of averaging or homogeneity of interest, knowledge, and resources [139]. In these studies the investment or resource cost associated participation is equally shared between those involved in the collective action. Oliver and Marwell changed this assumption, by introducing heterogeneous resource distributions, such that actors can invest different amount towards the provision of a public good. This section describes how Oliver and Marwell expanded on the existing framework of the formal theory of collective action, and how challenging the homogeneity of actors led to the development of the theoretical concept of critical mass.

Oliver and Marwell develop their theory of critical mass in three separate papers [116, 139, 140]. All three revolve around the idea that often in observations of collective action, a core group of highly resourceful and motivated actors can kickstart the provision of the collective good by providing start-up costs, or by passing some critical threshold of number of participants beyond which others will join too, i.e. the *critical mass* [139]. In previous studies of collective action, the resources or costs were equally divided among those actors that invested in the provision of a public good, as the profits were also equally shared and actors would only invest more than others if they could also expect a larger individual profit. By considering the interest or resources in populations as heterogeneous, individual contributions can differ, and therefore a group of highly interested or resourceful individuals might be able to form a critical mass, even when the mean level of interest in the population is low. To study under which conditions such a critical mass forms and influences collective action they explore the effects of heterogeneous populations in combination with production functions [139], group size [140], and social networks [116].

To investigate the effect of critical mass on the rest of the population, the decisions of actors need to influence each other in a model. Before the studies of Oliver and Marwell it was largely assumed that actors made their decisions in isolation and independently from others [116, 139]. Because of these previous assumptions, researchers were able to extrapolate group outcomes through the analysis of a single

individual. Oliver and Marwell take a different approach by making the choices of the actors *interdependent*, achieved by sequentially letting each actor decide whether to participate or not, taking into account how much has already been contributed by others. The interdependence of the actors decisions is necessary to formulate the theory of critical mass, as such a mass can only convince the rest of the group to join if not all decisions to participate are made at the same time. One key assumption that is inherited from the study of collective action is that the actors have access to all information about the provision of the public good, such as the total contributions up to that point and the involved costs [139].

Oliver and Marwell then study the effect of production functions, which describe the efficiency of subsequent contributions to the collective good. In the simplest case a production function is a first order linear function, such that every contribution is as efficient as the previous and the investment that an actor makes contributes equally towards the production of the good. Previously production functions were largely assumed to be shaped like logistic functions (s-shaped), such that early contributions first become increasingly effective, but further contributions past a certain point become decreasingly effective. In other words, the first 100 participants are more important than the last 100 if the production function is logistic. The shape of these production functions, such as accelerating or decreasing, change the conditions under which collective action becomes a feasible outcome [139]. One problem with these production functions is that they are hard to measure or detect in the real world, particularly in the context of collective rebellious actions such as protests and riots, and are therefore less relevant than the effects of group size and networks covered in the other studies of Oliver and Marwell.

In the second paper, Oliver and Marwell investigate the effect of group size. The formal theory of collective action predicts that smaller groups can more easily cooperate and coordinate, because of the overhead costs involved with the mobilisation and coordination of individual. As the group of participants grows larger, more coordination and effort is necessary to organise the involved individuals, resulting in overhead costs associated with group size. As these overhead costs associated with larger groups cut into the individual benefits, smaller groups are more effective in producing collective goods according to the formal theory of collective action. Empirical research into collective actions find the opposite; group size is positively related to the probability that a group will engage in collective action, particularly in the context of protests and riots [178, 179, 180]. Oliver and Marwell resolve the inconsistency between observations and the predictions of the previous



## 1.4 The Theory of Critical Mass

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models of collective action, by considering overhead costs as constant with group size [140]. Larger groups should then more frequently engage in collective action, as they have more total resources available, and can therefore also more likely form a critical mass.

There are two additional reasons why larger groups might more easily be able to form a critical mass when considering heterogeneous resource distributions. In homogeneous groups every actor is interchangeable, and the collective action outcome is a simple function of how many people participate. If populations are considered as heterogeneous instead, both how many and which actors are included in the participation become important, since once actor may be willing and able to contribute much more than another [116]. The first reason that larger heterogeneous groups can more easily form a critical mass, is that there are both more actors with high (and low) resource or interest levels compared to smaller groups. A larger group of actors more willing to commit to the collective action ensures the achievement of the critical mass. The second reason is that if the critical mass consists of a minimum threshold of required resources, a larger group can provide that critical mass with fewer individuals. Moreover the critical mass then involves less people, such that the organising costs and complexity associated with the collective action are then also lower in larger groups [140].

The introduction of group heterogeneity also led to an important shift in thinking about collective action and the centrality of solving the free-rider problem:

"The problem of collective action is not whether it is possible to mobilize every single person who would be benefited by a collective good. It is not whether it is possible to mobilize everyone who would be *willing* to be mobilized. It is not even whether all the members of some organization or social network can be mobilized. Rather, the issue is whether there is some social mechanism that connects enough people who have the appropriate interests and resources so that they can act. Nor is the existence of a large mass of free riders any particular hindrance to the mobilization or success of a movement. What matters for successful mobilization is that there be enough people who are willing to participate and who are also reachable through social influence networks." [140]

This shift in thinking is especially important in finding the context in which protests and riots occur. It appears that not all members of a disadvantaged group

have to be involved in a demonstration demanding change for that particular group. To find the contexts in which these movements emerge the focus needs to be on how the critical mass forms, not on how to mobilise everybody and overcome the free-rider problem. Once the critical mass forms then other people can engage and form the civil disturbance. Specifically for protests Oliver and Marwell wrote that the presence of an aggrieved minority in the population, with good education or political consciousness, seemed to be an important condition for these movements to emerge [140].

Finally to formulate their theory of critical mass Oliver and Marwell finish their trilogy with an investigation into network structure, specifically looking into network density, centrality, and communication costs. They find that denser and more centralised networks both facilitate collective action [116]. They also introduce costs of communication along these networks, which can be overcome by a higher mean resource level in the group, or increased group heterogeneity. Throughout these three papers on the concept of critical mass Oliver and Marwell highlight the importance of population heterogeneity on fostering collective action. Their final conclusion however, is that heterogeneity only helps when the mean resource level in the population is low. In groups that have a high resource level, heterogeneity hinders collective action by introducing actors with low resources.

# 1.5 Bounded and Beyond Rationality

Another important step in rational choice theory, having a wider impact beyond the study of collective action, is the introduction of bounded rationality. In the economic theories of collective action and critical mass and generally in rational choice theory, actors are given full information in order to let them make fully rational decisions. This is also one of the reasons why in the early studies of collective action the behaviour of a single actor could be extrapolated to the whole group, because all the actors had the same information available so they would also make the same decision.

In the real world individuals often have to deal with a lack of information or uncertainty when making decisions. In order to account for this using the framework of rational choice, researchers therefore proposed the concept of bounded rationality. In bounded rationality actors are not fully rational, but are limited in some way, for example by the amount of information or by cognitive limits. This would then explain why individuals make decisions that are globally irrational, but to the individual (locally) appear to be optimal.

Spreading and dividing information among actors leads to the study of coordination problems in collective action, especially when participants do not want to share their information with others prior to working together and have to reach consensus in a single round of discussion [158]. Within such coordination problems the importance of minorities has been highlighted, as sometimes despite their smaller relative importance they can still induce global changes [202].

Although the rational choice framework is useful for explaining in which contexts individuals might come together to collectively provide an economic good for themselves and others, it is less appropriate for describing why individuals might engage in acts of collective hostility and violence. Events like riots consist of crowds where there is some form of cooperation and coordination towards achieving a common goal, and therefore qualify as collective actions. In the economic theory of collective action, the final outcome is the provision of a public good that can be accessed by everyone, regardless of they participated. Riots however are not uniquely associated with public goods that hold a positive value. The main positive aspect that is potentially achieved through the use of civil violence is some form of (societal) change, improving the position of the group represented by the participants. However, the use of violence can also lead to negative outcomes, such as regulations

that induce more restrictions on freedom, and the potential formation of negative views towards the represented group. Moreover riots are also associated with the destruction of both private and public property [120], which further discount the value of the public good. Collective action theory can therefore not explain the provision of a public good through the use of violence, especially in cases where the same or similar positive outcomes can also be achieved through peaceful methods that are inherently less costly.

Some studies of rational choice and collective action disregard the effects of public rewards and costs to explain the use of violence, despite their magnitude [130, 142, 212]. They assume that public incentives and costs are unlikely to influence the choice of most actors, as self-seeking actors are only motivated by the benefits and costs that directly affect themselves. The underlying reason is that in these studies the contribution of an individual actor to the probability that the collective action will occur is considered to be negligible, and the actors therefore are not motivated by possible public rewards associated with that collective action. In the absence of public rewards, these studies include private benefits that the actors could gain from participating in the collective action, such as improved (social) status or income [130, 212]. Mason for example explains rioting behaviour as individual contributions of looting that result in private gains for the actors [118], but also concludes that rational choice models of collective action have trouble accounting for the full range of behaviours in riots. Mason's model predicts that actors only engage in looting if there is already a riot in progress, but in combination with the assumption that all actors are homogeneous, it cannot explain the initiation of a riot. Moreover these studies do not address other forms of common riot behaviour, such as the car burnings in Paris 2005 and Stockholm 2013 [170, 171], that do not result in specific private or public rewards. This would lead to the conclusion that either the proposed models are wrong and need to be improved further, or that some aspects of rioting behaviour are not (fully) driven by processes of rational decision making.

Rational choice theory is similarly unable to explain the use of violence in other forms of violent civil unrest such as rebellions. The key difference between riots and rebellions is that in riots the targets of violence are situational and local to the unrest, whereas in rebellions the participants aim to cripple, and finally overthrow and replace, the government or power structure in charge. The contrast between rewards and costs are amplified in rebellions, as the average citizen who participate collective rebellious action has almost nothing to gain, but everything to lose in terms of material rewards and possessions [130]. In an attempt to rationalise the decision for

## 1.5 Bounded and Beyond Rationality

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an actor to participate, rational choice models include an private psychological reward in addition to other public and private benefits [111, 130]. By participating in riots and revolutions actors risk injury or arrest, and in the worst cases torture, disappearance or the death of themselves and those associated with them, such as close friends and family, which all translate into extremely high potential costs [111]. Therefore, even when including private or other incentives in whatever form, participation in collective action in high risk situations such as rebellious activity cannot be explained by rational choice theory [111], as the benefits of collective action will not stand up to such grave risks.

The problem with describing the use of violence in rational choice models of collective action are the underlying mathematical restrictions. The instrumental approach to break motivation down all influences into strictly two categories of rewards and costs, and subtract them to obtain an (expected) net gain or loss, oversimplifies important concepts such as expression of grief and fear relating to risks of injury, and the interactions between them. Alternative approaches where rational decisions are bound by situational conditions such as  $P = S \cdot M$ , where  $P$ ,  $S$ , and  $M$  are all between 0 and 1, and  $P$  is the probability of action,  $S$  is the safety of participating, and  $M$  is the (rational) motivation to join, are not possible or used within the framework of rational choice. Instead risks and safety are factored into the potential cost of joining. In rational choice framework the rewards always have to be larger than the costs to explain why individuals engage in collective action. As the potential costs of joining become high with risks associated with facing repressive repercussions, all kinds of incentives have to be added to the reward to make participating in violent acts a rational choice. This approach consequently leads to the risk of internalising behaviour, where the group outcome no longer emerges out of the model, but is hardcoded into the preferences of the individual actors in order to explain the observations [111].

As the rational choice framework ultimately describes the difference between the rewards and costs of participation, it relies on the (relative) quantification of these concepts, which might not always be possible. The value of some public goods such as neighbourhood cleanups can be easily obtained by comparing against commercial services that perform the same service, and the investment and material costs of the individual participants can be calculated by some average salary per hour multiplied by the invested time, added to the cost of a broom. For riots, the public value of societal change or reduction of discrimination are more abstract concepts, which do not have a straightforward (monetary) value that can be calculated. Similarly the

various private (psychological) rewards that need to be added to make engaging in violence a rational decision do not hold a specific value that can be (rationally) calculated to offset the risks and costs associated with participating in violent collective action. An alternative approach to describe the motivation of individuals to join in collective actions like protests is offered by social psychology, which revolves around the interdependence of individual decisions and behaviours and those of the group, and is not explicitly anchored in the assumption that human behaviour is driven by rational decisions. At the end of the next section I integrate and unify these two perspectives.

# 1.6 The Social Psychology of Protest

Rational choice and critical mass theory are sociological theories, aimed to explain under which conditions collective action occurs or is hindered. The rational choice framework is grounded in economics, and uses cost/benefit ratios as a generic framework to describe when individuals are compelled to participate in collective action. While it may explain why some movements occur, it is generally unsuitable to explain important social processes like solidarity: people sometimes help other individuals without expectations of reciprocal behaviour or other rewards, which would thus be irrational [155]. Social psychology on the other hand is concerned with the motivations of individuals for certain behaviour and the influence that individuals exert on others. By focusing on interactions and individual reasons as to why people join protests and demonstrations, theories of social psychology can explain irrational behaviour that cannot be captured by rational choice theory, which instead rely on a model of costs and benefits for studying the decisions of individuals.

### 1.6.1 Collective Identity

Central to explanations of social psychology for why individuals are compelled to participate in protests and other forms of rebellious collective action is the concept of social or collective identity. This term was first introduced by Tajfel, who differentiated between a personal and a collective identity, and that it could be the main sociopsychological process fostering participation in collective action [193]. Social or collective identity is defined as the part of a personal identity which is derived from (the knowledge of) membership of the group(s) an individual belongs to, together with emotions and values attached to that membership [65, 175]. It may be imagined or perceived rather than experienced directly [155], and may form an important part of a personal identity [155].

One consistent finding has been that the more an individual identifies with a certain group, the more inclined that individual is to join in a protest on behalf of that group [65, 92, 184, 221]. Those with a stronger relationship with the group will put more effort into improving the situation of that group [65]. The cooperation within a group results from the interchangeable, mutual, and shared perception of the members. Collective identity has therefore also been regarded as a group resource with the ability to mobilize members of the group into collective action or recruit more members into a movement [175].

However there has been disagreement to which degree identity is explained, or can be explained by the participation in social movements and protests [111]. Likewise collective identity does not always precede, but instead is formed as a result of or through collective action [155]. For example taking risks in acts of collective action might be explained by the prior investment and commitment of individuals into the collective action and social movement, and retreating instead could irreversibly violate their identity. Taking risks and potentially making sacrifices then likely heightens the sense of belonging to the collective leading to a redefinition of the individual identity, and can make future participation more intense and persistent [111].

Several studies have found that a *politicized* identity is a better predictor of whether an individual will engage in collective acts such as protests than the overlap between individual and collective identity [65, 92, 155, 184, 221]. Individuals that have a politicized identity are aware of the existence of shared grievances, and moreover take it as their duty to improve the status of a group or other negative aspects associated with the collective identity. This alters their association with the group towards an association with a social movement, and makes them more likely to engage in protests. Regarding acts of self-interest as the opposite of moral actions, political activism can be a way for individuals to construct a (more) desirable self [155]. The politicized identity can therefore transform into a personal identity project [221], and also gives people a sense of agency, i.e. that they have a choice and are able to exert influence on their environment by doing so [53]. Through this process politicization has the potential to channel and engage broad identities into specific social movements, by changing identification with a group to identification with a movement [221].

Identity is not the only reason why individuals are compelled to participate in protests. Many people identify as part of a group but still do not take to the streets to demand change. Therefore the motivations to demonstrate must also come from other sources, for example grievances and inequality [184]. The social psychology of protest focuses both on finding these sources of motivation, as well as describing the relations between them in order to unite or integrate them into a single framework [221]. Collective identity often takes a central place in these frameworks, acting as glue between the different motivators.

This approach has led to criticism, for example according to Polletta collective



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identity has been treated both too broadly and too narrowly, or is sometimes treated as a residual category for behaviour that cannot be explained otherwise [155]. Indeed the collective identity of the group has been theorised to influence strategy, emotions, relations, interests, and collective action amongst others [65, 92, 111, 155, 175, 184, 221]. Van Zomeren demonstrates in his meta-analytical overview of more than 180 studies how collective identity, efficacy and injustice are interrelated and how they all three uniquely correlate with collective action [221]. In this framework identity then does not only have a direct impact on collective action, but also indirect effects on feelings of inequality and injustice and group efficacy.

Social identity can also help explain why people stop participating in protests and social movements. According to Polletta, one of the main reasons why individuals cease to engage in demonstrations is that their collective identity stops lining up with the movement [155]. For example when demonstrations turn violent others might no longer want to be associated with those that engage in altercations with the police. Another reason why participation might decline is that individuals feel that their identities and concerns have been sufficiently represented [155].

### 1.6.2 Grievances, Deprivation, and Framing

One of the main reasons that individuals engage in protest is to express grievances and frustration, for example regarding their socio-economic situation [184]. Demonstrations can also be expressions of celebration, for example the gatherings that took place following the failed coup in Turkey in July 2016 [195]. More often though they are about demanding changes or are against a certain measures of the government that will have (perceived) negative effects. Many individuals are unsatisfied about their life in one way or another, but protest occur often specifically as a group activity. Therefore social psychologists focused on grievances that were shared by the group.

This led to the theory of group deprivation, that offered a better explanation for the participation of protests than individual or egotistic hardship [221]. In the case of riots however, specifically the race riots in the 1960s in the USA, it was found that deprivation is a very bad predictor of violence [143, 144, 178, 179, 180]. Not just fixed relative deprivation, but also widening gaps between groups were not good predictors of the violence that occurred in this period.

What was found was that more than objective deprivation, the subjective perception of group deprivation was a more powerful predictor of collective action, leading to the theory of relative deprivation [92, 184, 221]. Sometimes inequalities between groups can (temporarily) be perceived as fair and accepted, and therefore the interpretation of the differences between groups is more important than the factual deprivation. Collective action is therefore only likely when differences between groups result in a subjective sense of injustice in the deprived group [221].

Even more important than the interpretation of group-based differences are the emotions resulting from possible injustices (affective injustice). Researchers have found that emotions that are the result of perceived injustices (e.g. anger) are a better predictor of collective action than the cognitive interpretation of inequality [65, 221]. A stronger association with the group results in stronger emotions from perceived group deprivations [65, 92, 111, 155, 184, 221].

Researchers have made a distinction between two types of group-based disadvantages: structural and incidental [221]. Structural disadvantages are those that are derived from being member of a group, such as for example the relative deprivation of certain minority groups. Incidental disadvantages are situation or issue-based, for example an increase in tax or tuition fees.

In order to overcome structural disadvantages a collective identity must be transformed, whereas for incidental disadvantages a new collective identity has to be formed [221]. This relates back to the observation that collective identity not always proceeds a protest, but rather can be the outcome of such a collective action [155].

The success for recruitment into social movements therefore relies on the efforts to strategically *frame* a collective identity with which the people that are affected by the incidental disadvantage can relate [221]. Such frames are often built upon existing independent collective identities [155]. In cases of structural disadvantages a well established collective identity can still be framed differently to the public, as groups might present themselves differently outwards than they would do within the group (e.g. more united or homogeneous). Often as part of the frame, 'the opponent' is also represented as a collective identity, and often refers to human decision makers of some sort rather than impersonal forces (e.g. climate change or segregation). However such a frame can also create a backlash and incite a counter movement by those opponents, as they potentially feel that they are attacked and need to defend themselves. Sometimes counter movements can be stronger than the

original movement that made the frame [155].

### 1.6.3 Efficacy

Emotions and inequality alone cannot explain collective action: structural inequality is present over large timeframes which can leave members perpetually aggrieved, but protests about those situations only happen incidentally [221]. In order to transform the disadvantaged status of a group and collective identity to a normalised one the members of the group need to believe that it is possible to achieve this transition, or that engaging in protest will work towards achieving this goal. The recognition of this possibility has been described as efficacy [92, 155, 184, 221].

More important than efficacy is group efficacy, the belief that injustices can be overcome through a united effort by the group [221]. An important empirical example is the 1964 Mississippi freedom summer project, where volunteers came to Mississippi to help register black voters, and build and staff freedom schools. Groups of friends often decided to participate together. Participants felt that going together would be more efficacious and withdrawal would be embarrassing if others had the commitment to persist [71, 119]. Group efficacy leads to a sense of collective strength or power, meaning that the stronger the subjective sense of group efficacy is, the more likely individuals are to engage in collective actions like protests [221].

Similar to deprivation, the actual efficacy of a group does not matter as much as the perceived efficacy. Another important factor for efficacy is political opportunity: sometimes exogenous factors can create an opportunity for change increasing efficacy of the group or temporarily endowing the group with more resources. Moreover politicized identities also increase the perceived efficacy of collective action. Social identity is related to efficacy by giving low status group members a sense of empowerment [221].

### 1.6.4 Social Embeddedness

In addition to the concepts of social identity, deprivation and emotions, and efficacy, the concept of social embeddedness has also been proposed as an important component that individuals factor in when deciding to participate in a protest [92]. The argument is that decisions to participate are not taken in social isolation and

that the relations specific to the individual need to be taken in account [120]. Van Steenbergen and Klandermans argue that it is within and through these social networks that the processes of the formation of grief, group-based emotions, social identification, and perceptions of efficacy are synthesised into the motivation that prepares people for participation.

Social embeddedness is proposed to consist of three primary components: 1) a structural component referring to the actual network structure that an individual has, defining the connections to other individuals; 2) a relational component categorising those connections (e.g. friend or family); and 3) a cognitive component, that is qualified by shared interpretations and opinions through these connections [92].

The concept of social embeddedness actually relates to the theory of critical mass, where the relative positions of individuals in a network determines the outcomes for collective action. Individuals who are connected to friends or acquaintances that are highly motivated themselves are more likely to become a part of the social movement [71, 116, 184]. Conversely highly motivated people might be deterred from taking action due to a lack of support from those surrounding them, giving them a lower perception of efficacy.

Personal ties and social embeddedness are important in the context of extreme repression, because they provide the social fabric required for effective resistance to the state. Usually the density and insulation of these networks prevent infiltration from outsiders, and additionally create a lack of anonymity, increasing individual accountability and preventing defection. Social embeddedness in these networks is therefore one of the main factors driving sustained collective acts of rebellion in high-risk situations [111].

### 1.6.5 The Social Psychology of Protest and Violent Collective Action

The theories that describe the social psychology of protest and the economic theory of collective action are two different frameworks that each have their own benefits in describing how collective actions such as could riots emerge. One considerable difference between the two is that the social psychology of protest does not explicitly describe the use and occurrence of violence, whereas the rational choice framework in the theory of collective action has been applied to riots and rebellions (e.g. [111,

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118, 130, 212]). Despite the strict definition in Section 1.2, not all protests are free of violence regardless of the original intention, and riots sometimes directly evolve out of (peacefully intended) protests (e.g. London 2011 [121]), implying an overlap in the motivation to join in protests and riots. I explain how the two frameworks that have been set up by the researchers that proposed these theories can be unified and integrated into a mathematical model.

The economic theory of collective action and the social psychology of protest are both similar and different. Some of the concepts developed in both theories directly overlap, others are comparable but not the same, and for some concepts there are no equivalent or relatable counterparts. The greatest distinctions between these (collections of) theories are the underlying assumptions and approaches which the researchers have employed, which consequently resulted into two different frameworks. The goal of the two theories is similar, as they both aim to explain the rise of certain collective actions, find what drives and motivates individuals to participate, and how these motivations are influenced by others and the group. The key difference in the assumptions between the two theories is that the economic theory of collective action assumes that the decisions of individuals are, or can be explained by, rational processes, whereas the sociopsychological counterpart is not explicitly anchored in this assumption. The social psychology of protest therefore includes concepts like perceptions, beliefs, and emotions, that influence the motivation and decisions of individuals, and are not necessarily rational or correspond with the real world.

The theory of collective action has links with the academic discipline of sociology, and uses rational choice theory as the instrument to explain the decision of individuals in order to study the conditions that lead to the provision of a public good. Consequently this has led to the development of a framework in which all possible influences on the decision participate are expressed into two categories; rewards and costs. These two categories are then subtracted to obtain a (expected) net gain or loss, determining the action of the individual. Researchers that employ this framework use it to explain under which conditions individuals come together to provide a public good through a collective action, and alter the (kinds of) rewards and costs the actors in these models experience to explain observations from the real world.

The social psychology of protest is not specifically focused on describing or predicting whether collective action will occur or not. Instead it aims to find the different influences that motivate individuals to engage in protest, and how these motivations are influenced by others and the group. Their methods are largely

based on surveys and questionnaires (e.g. [221]), as opposed to inferring motivations from an analytical framework that is used to calculate the decision of an individual and the group. The researchers in this field propose multiple distinct concepts, but simultaneously integrate and unify them into a single framework by explaining how they relate and influence each other and the individual (e.g. [221]).

Despite the different approaches and assumptions, parts of the two frameworks have considerable overlap and similarities. For example, researchers from the social psychology of protest have proposed that individuals with a politicized identity are more likely to take action, because they take it as their duty to improve the status of the group [92, 184]. It is also a way for some to construct a desirable image of themselves, and can therefore become a personal identity project [221]. The same concept in the rational choice framework are the private psychological rewards that have been proposed to rationalise the decision to join in rebellious activities, as both disciplines describe the motivation for participating as a way to improve the self-perception of an individual.

An example of concepts across the two theories that are similar, but the same, are social embeddedness and critical mass. The improvement of the framework used in collective action to let the actors make their decisions sequentially rather than simultaneously, combined with heterogeneous interest distributions in the public good, enabled Oliver and Marwell to develop their theory of critical mass from 1985 to 1988 [116, 139, 140] (see Section 1.4). They also removed the central focus on the free-rider problem, noting that the mobilisation of every possible participant is not necessary to achieve collective action, and that those who opt to remain passive and benefit from the collective action do not form hindrance in achieving a successful movement. Through the introduction of the theory of critical mass, the location of the actors in the network became an important influence on the mobilisation of participants for collective action. This is similar to the concept of social embeddedness shown by Klandermans et al. in 2008 [92, 93], where the structure of the network also plays a role. Klandermans further highlights the qualitative importance of network connections, which Oliver and Marwell did not explicitly specify 20 years earlier when they simulated the importance of contact networks.

Efficacy is a concept that is explicitly developed within the social psychology of protest, but is only implied in the rational choice framework of the study of collective action. In social psychology efficacy is described as the (perceived) belief that the protest will lead to the desired change. Two different and related forms of efficacy

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can be found within the rational choice framework. First is the contribution of the agent to the collective action and the provision of the public good. In some studies the actors have do not believe that they can exert any influence on the provision of the public good (e.g. [130, 142, 212]), and therefore only join for individual rewards. Other studies however propose that the attraction of the public reward is a necessary component to make rioting a rational decision (e.g. [118]). The second way in which efficacy is implied in rational choice theory is the expected yield, which compounds the probability that collective action will occur and the net gain or loss. The expected yield factors in the possible risks and costs associated with joining in collective events of civil unrest in rational choice theory, which are not described in social psychology. Efficacy in rational choice theory, unlike group-based efficacy in social psychology, is not about the appropriateness of the method or collective action, but is about the individual effectiveness of participation. Individuals can simultaneously believe that a protest might be effective and will lead to the desired social and political changes, and also suppose that their contributions are negligible, or that it will not be rewarding or too risky for them to participate.

The largest difference between the two frameworks of rational choice and social psychology are the concepts of emotions and collective identity. Participating in collective actions such as riots could be interpreted as an expression of emotion, and hence be linked to the private psychological rewards proposed by the economic theory of collective action, but this is not explicitly specified by rational choice models. Similarly the role of collective identity is not described within rational choice theory, since it does not link to either a cost or a reward. This highlights the limits of the rational choice framework, as the social psychology of protest shows that there are influences that cannot be simplified to either a reward or a cost, yet are important influences in the decision to join in collective actions of civil unrest.

Both approaches of social psychology and rational choice have their own benefits. Whereas the social psychology approach describes a wider range of distinct influences and their qualitative relations and includes the effects of the group on the individual, the rational choice method offers a analytical framework by which the group outcome of individual decisions and interactions can be calculated. The findings and methods from both frameworks can be combined into a hybrid approach, where the analytical framework of the economic theory of collective action is used in conjunction with the motivations of the individuals described by social psychology. This removes the (mathematical) restrictions imposed by the rational choice framework, and allows for different kinds of influences and interactions that drive the decision to participate.

Moreover, the relaxation of the assumption that all behaviour is rational does not invalidate an important contribution to the research of collective action, the theory of critical mass proposed by Oliver and Marwell [116, 139, 140]. The only requirements for the theory of critical mass are heterogeneous motivations in the population and interdependent (sequential rather than simultaneous) decision making, which are both important qualitative concepts in social psychology. The next section discusses the use of mathematical and numerical models in general and their benefits, which applies to the proposed combination of social psychology and a quantitative analytical framework. I also highlight different methodologies and specific examples to apply them to situations of conflict.



# 1.7 Mathematical and Numerical Models

The question of which conditions foster acts of civil disturbance has received attention from many, if not (nearly) all, of the large disciplines of social theory. Sociologists and economists have used the basic assumptions of rationality to build a framework to find out when violence occurs [142] and developed theories of competition [143], psychologists have focused on the motivations of individuals [184], geographers have studied spatial patterns of events [16, 17], political theorists have developed resource mobilisation theory to study social movements [215], and criminologists have focused on identifying who participates in riots and policing responses [149]. Despite more than half a century of research into collective action, including civil unrest, there is still a lack of understanding about the conditions that lead to riots, and how such events evolve in time and space.

Most of the research and theories from the social psychology of protest are accompanied by surveys or other forms of data, where the relationship between variables are inferred through statistical analyses. One way in which mathematical models can be used is by reversing this process. The relationships between variables are explicitly declared beforehand, and through the modelling process outcomes are obtained, which can then be tested against data and observations.

Mathematical models can thus be used to test hypotheses about human behaviour [130], such as those proposed by the social psychology of protest. Such methods should not necessarily replace statistical analyses, but can be used to complement and improve hypotheses testing, increasing their validity. An internal problem with the use of statistical analyses is causality. Correlations between variables describe the strength of a potential relationship, but do not give any information about what it consists of or its nature. If the measured variables can be manipulated then, at best, a causal direction can be inferred [221]. However as most of these studies rely on surveys, such manipulation is often impossible.

In mathematical models on the other hand, the causal or mechanistic relationships between variables are explicitly declared. The manipulation of variables is therefore no problem as different starting values can be used to obtain different outcomes. The model can therefore be treated as an experiment, where different initial conditions and processes can be used to explore various scenarios and causal mechanisms. Such models can therefore be treated as a substitute for laboratory

experiments with controlled conditions, which might not always be possible. Particularly in the case of human conflict, the use of violence and acts of rebellion are generally illegal, and such real-world experiments would very likely be blocked due to ethical concerns [130]. Moreover, events like riots are generally undesirable due to the possible damages they can inflict.

Because of the chaotic nature of events civil unrest and their relatively infrequently occurrence, gathering accurate data about the particular dynamics of riots is not easy. Most evidence is gathered from newspapers, interviews, surveys, and court accounts after these events have taken place [215], rather than from observations during the event. Models on the other hand can be used to run simulations of protests and riots, creating an alternative source of data. Simulations can then be used for example to discover how to best respond to different situations of civil violence [152].

Although human behaviour is subject to a multitude of endogenous and exogenous influences and can be seemingly very complex, many aspects of human behaviour can be captured by very simple mathematical descriptions, particularly in situations of conflict [87]. The idea of using mathematical models to capture human behaviour is not new. The studies that investigate collective action using rational choice theory, including Oliver and Marwell's theory of critical mass, use simple mathematical rules to describe the behaviour of the individual actors [116, 139, 140, 142].

Mathematical models have been used to describe various forms of conflict: Lanchester theory for example describes a set of rules that predicts the outcome between two parties engaged in armed conflict [12, 102], whereas the Richardson model describes conflict escalation between two parties [19, 160]. Other models have looked specifically into revolution participation [98, 104] and armed revolt [12, 95]. One finding has been that success not only depends on initial force size, but also on support from the local population, and how that support changes with the use of (misguided) violence [11]. An explanation for why some political revolutions may come as a surprise, is that those who dislike the government may hide their desire for change as long as the opposition seems weak [98].

One of the first numerical models of civil violence was created by Granovetter in the 1980s [72]. This study explored the importance of costs and benefits to engaging in collective behaviour in the context of riots, and particularly identified critical thresholds which significantly altered the model outcomes. Such thresholds were later

## 1.7 Mathematical and Numerical Models

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used by Schelling to create (Schelling's) model of segregation, and lead to studies of 'tipping point behaviour', where model outcomes rapidly shift when running over a critical threshold [169]. Such patterns of critical behaviour relate to the theory of critical mass, where if there is a certain number of participants collective actions can catalyse into global movements. This behaviour has also been observed in riots and protests, where a threshold of minimum participants was detected under which violence failed to develop [47, 179].

Many of the mathematical models used in a rational choice theory and critical mass are analytical models. These models have an explicit solution that can be expressed symbolically. Another method is numerical or computer simulation. As models grow in complexity, it might no longer be possible to find analytical solutions, but numerical simulation can still be used to obtain the model behaviour. For example Oliver and Marwell supplement their analytical model for the theory of critical mass with numerical simulations because they could not find the analytical solutions [116].

Numerical simulations allow for much more complex behavioural rules and systems, and have therefore also allowed researchers to capture more complex dynamics such as riots. A wide array of techniques has been employed to demonstrate different aspects of civil unrest, including differential equations [24, 25, 35, 103, 104], agent-based models [28, 48, 55, 86, 129, 173, 174, 198], statistical methods [16, 17, 100], game theory [152], and grid-based models [17, 31].

However few of these studies answer questions about what influences riot behaviour. Instead they focus on for example the frequency of conflict [31] and how the frequency relates to food prices [100], without considering the differences between individual events. Some of the models using differential equations focus on solving conceptual problems and finding characteristics of a system, but fail to explain how for example the existence of 'traveling waves' relates back to riots or how this knowledge helps prevent civil violence [24, 25].

In agent-based modelling the focus is on the individual entities, so-called agents, that make up the model environment. These agents represent individuals or groups of individuals (e.g. families or organizations) and are given behavioural rules. The model behaviour is then obtained through the interactions of the agents with each other. A particular advantage of such models is that the behavioural rules can be relatively simple and easy to understand, whereas the model output derived from the interactions can be complex like the real world. This can also be described as

the concept of *emergence*, where complex global behaviour is obtained as a results of simple local individual interactions, but cannot be predicted from the individual behavioural rules.

The agent-based models of riots have been used to study for example the effect of jail time after arrests [55], the movement of individuals within crowds [198], and in particular have been applied to specific situation of the London riots [48]. Additionally such models have also been used to study in which particular network topologies repression is or is not effective [173, 174].

Other studies focus on a set of events in the same period, specifically on how violence spreads from one location to another. Evidence for (geographic) contagion and the predisposition of violence in certain cities have been under investigation particularly following multiple waves of race riots in the 1960s in the USA [143, 178, 179, 180]. Sometimes violence spreads directly (e.g. the next day) to other locations, becoming a part of the same event such as in the 2011 England riots. The disturbances that started originally in the borough of Haringey quickly spread to other parts of London, and later to other large cities in the UK such as Birmingham and Manchester. Improvements in statistical methods and numerical simulation have allowed for statistical modelling of the spatiotemporal patterns of diffusion of both the race riots that shook the USA in the 1960s and the recent London riots [16, 17, 131, 132].

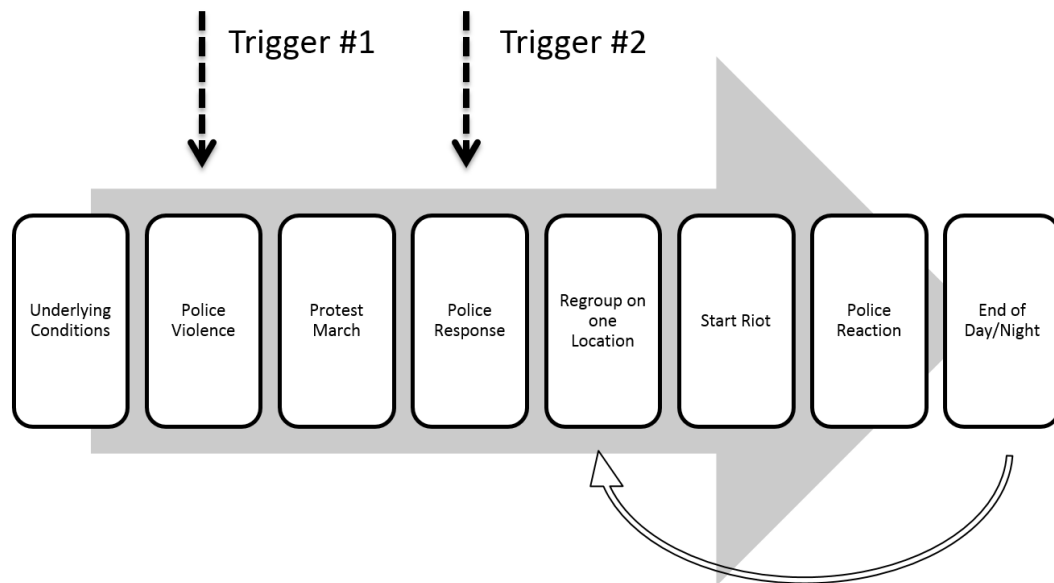
Complex patterns of contagion in for example the Arab spring [35] have also been simplified to two infection structures: 1) where violence in location A spreads to B, and 2) violence in location A cascading into another location C through B, where B then does not experience any violence [35]. These infection structures account for the majority of the diffusion behaviour during the Arab spring, and it can be shown using a relatively simple system of differential equations and linear couplings between potential violence locations under which conditions violence cascades from one location to another [35].

# 1.8 Riot Patterns and Trigger Events

In order to build a numerical model for riots, I describe a 'general riot' consisting of components that are commonly shared between individual instances of civil unrest. Figure 1.2 shows an overview of events during such a general riot. Prior to the start of any form of collective action, there are underlying conditions that cause grievances in the population of potential rioters. Then, as a result of some trigger event (e.g. an incident involving (perceived) excessive police violence), individuals gather in a protest march expressing their dissatisfaction regarding these underlying conditions. Given the formation of a crowd, the police responds to the protest march to ensure the safety and prevent escalation. During the protest march a second trigger can occur, for example through altercations between participants of the protest and police officers. This second trigger leads to an escalation of violence and develops into the riot. The main behaviour of the crowd transitions from voicing discontent into violence. Consequently the police behaviour then also changes, by responding to the emergence of the riot and dispatching (more / specialised) police forces, attempting to contain and end the riot. The police and rioters clash, until the rioters are dispersed and the event stops. Afterwards, the participants that are not arrested can regroup at a later time (either on the same or another day) to repeat the process, and also potentially attract others to join.

This general riot can then be divided as two separate phases of collective action; 1) a gathering of individuals preceding a riot, such as a protest march or a demonstration, and 2) the riot itself. The riot also consists of two phases, the emergence of the riot and the following police response, which dynamically interact until the riot stops and/or re-emerges at another location and time [120].

The first event of collective action in the general timeline of a riot, as shown in Figure 1.2, is a protest. Prior to the protest a trigger event takes place, that is in some way related to certain underlying conditions which are then addressed within the protest, and subsequently also in the potentially following riot. Different underlying conditions have been proposed and explored as potential predictors and causes for both protests and riots. A persistent and commonly proposed idea is that deprivation is one of the main underlying causes that give rise to protests and riots. However, both objective and relative fixed group-based deprivation, as well as widening economic gaps, were all found to be bad predictors of the occurrence of conflict [143, 144, 178, 179, 180]. Others theorised instead that economic competition, through economic



**Figure 1.2: General timeline of riots.** *Most riots start with some sort of trigger, for example an incident involving (perceived) excessive police violence. In response to the incident a crowd gathers in a protest march, demonstrating against the violence. During the protest civilians clash with police officers, creating a second trigger which escalates into further violence and starts the riot. The police responds to the riot, resulting in a dispersal of the participants, who regroup at a later time and location.*

opportunity and upward mobility of marginalised groups (i.e. narrowing economic gaps), leads to conflict between groups and consequently to civil unrest [143].

Due to a lack of statistical proof for these theories [178, 179, 180], researchers developed alternative explanations for why individuals join in these events. The social psychology of protest proposes that, in addition to (perceived) efficacy and collective identities, emotions of e.g. grief and anger play a role in the decision to join in protests [92, 184, 221]. These emotions relate to (perceived) group-based injustices, which can include issues like social exclusion, segregation, and also group-based (relative) deprivation. What separates the theories of emotion and deprivation is that in the first, individuals need to be aware and perceive these issues as being group-based, as well as being unfair, whereas the latter was (initially) based on population and income data.

In some cases riots can be traced back, or are attributed by the media to have started with, a single event. Such events are sometimes denoted as ‘triggers’ or ‘trigger

## 1.8 Riot Patterns and Trigger Events

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events'. Sometimes such triggers are obvious singular events, but they can also be the result of the accumulation of actions that help trigger the riot, such as in the Istanbul 2013 riots, where repeated police interventions resulted in backlashes from protesters [203, 204]. Trigger events sometimes relate to incidents of (perceived) excessive use of police violence [114]. The three major riots of Paris 2005, London 2011, and Stockholm 2013 can all be traced back to an incident where a civilian was killed by police [121, 170, 171]. Also all three cases involved individuals who are considered to belong to a minority group. Likewise the death of several members of the black community in the last 5 years in the USA during attempts at arrest have resulted in civil unrest (e.g. [189, 190, 216]).

There is much uncertainty about the nature of these trigger events, and why some events lead to protests and outbursts of violence, and other similar events do not. One possible explanation for why collective action is induced by a trigger is that these events can symbolise (structural) underlying problems, and can influence the formation of collective action through the attention it generates. They can (temporarily) act as a gateway through which societal issues can be introduced and discussed in the media, and provide an anchor and reference point around which the public and political discourse can be centralised. Through the attention for these events, the general public becomes aware of these issues, or is reminded of their presence. They can also induce and reinforce the realisation or perception of individuals that some of their problems are not personal, but are group-based instead. This process could then solidify the sense of a collective identity, and heighten emotions related to these group-based (perceived) injustices [221], and consequently increase the potential group size for a protest, resulting in a higher probability for collective action [140, 178, 179, 180].

The combination of the underlying conditions and the trigger event provides the opportunity to build a frame that can be used to motivate people into joining in collective action such as a protest, and consequently give rise to the initiation or expansion of a social movement. These frames often consist of a strategically chosen collective identity, to which people affected by the trigger event, or others with similar grievances, can relate [221]. Therefore such frames are often built upon existing collective identities [155], but might be presented differently as part of the strategic considerations. Moreover, through the symbolisation of the underlying issues, trigger events can also lead to the inclusion an 'opponent' in the frame [155]. Such opponents are often personalisations of the abstract underlying issues, such as segregation and social exclusion, for example in the form human decision makers who

are claimed to be responsible for these circumstances. These opportunities offered by the trigger event to build the frame can therefore help unite individuals through the proposed affected collective identity, and channel their grievances towards the framed opponent, giving rise to collective actions like protests and possibly following riots.

Not all protests develop into riots, but riots are often preceded by some form of gathering or demonstration. One survey of different events found that 50% of riots were preceded by forms of collective action that initially started out as non-violent, but escalated into violent clashes [120]. As the theories from social psychology showed, collective identities are formed as much outside as through acts of collective action [92, 155, 184]. Protests prior to riots can therefore have an significant impact on the potential for violent behaviour [120]. For example participants can get a (false) sense of confidence and support from those around them, raising their efficacy and potentially making them more prone to engage in extreme and violent behaviour.

Riots sometimes directly evolve out of clashes between protesters and police [120]. Peaceful protests can be perceived by governments as a threat and a potential start for civil unrest [115], and commonly the severity of the threat is measured by the size of the crowd [120]. Larger crowd sizes, violent or not, can lead to more aggressive police responses, exacerbating the potential for civil violence [115, 120]. Events with large crowds present a special situation for police forces. Normally when responding to incidents of urban crime perpetrators will flee and are generally outnumbered by the police. During protests however, the police is usually outnumbered by the participating individuals, therefore posing a significant risk if there are outbreaks of violence. Most riots begin on weekday evenings or weekends, peak during late evenings hours, decline to virtual inactivity from early morning to noon and then gradually increase again, like a diurnal cycle. The peak riot activity generally occurs between early evening (8-10pm) and midnight [2, 120].

There are also cases where demonstrations preceded riots, but the outbreak of violence did not directly follow from the protest. During the Stockholm 2013 riots for example, there was a pause of two weeks between a protest march against the death of a civilian as a result of police action and the outbreak of mass violence [170].



# 1.9 Contact Networks and Social Media

Particularly after the 2011 events of the Arab spring and the London riots there was much attention in the media on communications through online social networks (e.g. [14, 21]). The general underlying theories were that these events were facilitated and exacerbated by the unprecedented opportunities that online social media offered to individuals to communicate and share information [80]. The dense online communication networks according to these theories enabled both the spread from one location to another, as well as allowing individuals to self-organise into large protests in those locations.

Before the arrival of online social media and the Arab Spring and the London riots the importances of social networks in riot behaviour, in particular the mobilisation of participants, were already recognised [71, 90, 116, 175]. The development of the theory of critical mass in the 1980s, for example, already highlighted the importance of network configurations. Most of the studies that investigated the role of the network configuration as a variable considered very simple network structures and varied simple macro descriptors, such as the density and centrality of a network.

The general consensus is that more connections within a network facilitate collective action [71, 90, 116, 173, 174]. The higher number of connections between individuals help in disseminating information more quickly through the network and decrease costs associated with mobilisation, leading to a higher probability of collective action. The reverse effect has also been observed, where sparse networks are associated with a higher frequency of conflict. In a particular case for Thailand, a study demonstrates that the sparseness of the network between anti Thai government organisations prevents cooperation. Each organisation therefore initiates their own actions, leading to a higher incidence of conflict [123].

The rise of online social networks has enabled researchers to map out the structures of human contact networks in greater detail, which previously took much more effort. Without the use of technology researchers had to depend on surveys, asking individuals about to detail their own contact network. One problem with such surveys is that not all relationships are recognised by both parties. Other efforts to understand the topologies of human contact networks were made by studying analogues, such as phone networks and the exchange of Christmas cards [79].

Studies that use human contact networks in numerical models have two options; 1) use an existing network and be tied to a fixed population size, or 2) generate a network using an algorithm. Because the social relations of an individual play such a big role in determining the participation for collective action, the topology of the network can have an important role [175]. Yet most of these algorithms describe simplified versions of human contact networks, each with their own characteristics. Some are very simplistic and based on geometric shapes, such as ring and star networks, others are more complex and target specific properties that are found in human contact networks, such as scale-free and small-world networks [3, 211]. Siegel uses four of such simplified topological structures to study the effectiveness of repression responses from the police [173, 174]. Because online social media has led to more insight into the structure of human contact networks, other alternatives are now available, where the key descriptors of such a network can be used to generate another network at arbitrary size matching those descriptors, such that numerical models are no longer tied to oversimplifications of human contact networks [94, 167].

Others studies focus specifically on how such networks are formed and maintained. Human contact networks are the product of interactions, and preferences of individuals can shift over time, changing relationships and altering the network structure [29]. The dynamic component of networks in numerical simulations is not very often addressed as the contact networks are assumed to remain fixed, because changes in network structure likely happen over larger timeframes than the modelled events. On the contrary, events of collective action like protests and riots can also be a reason for individuals to form new connections with other participants.

Studies of networks not only focus on structure, but also what is shared along the connections between individuals. It was already posited in 1947 that rumours that spread by individual contact were central to the development of violence in riots [215]. Singer provides a detailed account how individuals learned about the unrest in the 1967 race riots in Detroit [176]. Of those who were arrested 40% found out about the event through interpersonal contact, 10% by phone, 25% from direct experience by being present, 15% from radio and 10% from television. This highlights the importance of relationships between individuals for the propagation of such information. One other study though posited that implied networks related to mass media were responsible for the spread of violence [131].

Online social media allow for accurate tracking of messages (posts on Facebook,

hashtags on Twitter), such that information flows can be analysed (e.g. [110]) and spatial and temporal spread can be mapped out [22, 62]. A study into protests in Spain in 2010 revealed that the popularity of the hashtag related to the protests rose in the shape of a logistic function. There was little increase in the period prior to the announced protest, but shortly before rose in popularity, rising stronger after the event had happened [70]. Additional to analyses of such online interactions there have also been attempts to model the spread of behaviour and recruitment patterns in online social networks [42, 188].

The study of information traffic and spread has also led to attempts to predict potential upcoming events by trying to discover and detect early warning signs from social network activity and news [80, 97, 156]. In one study for example, it has been found that events were often preceded by a spike in online conversations [80], and that variance and autocorrelation of hashtag frequency, i.e. the frequency by which something is mentioned, increased just before a critical transition in social network activity [97].

## 1.10 Research Questions and Motivation

One observation from the previous literature is that the majority of studies using numerical models to describe riots do not compare model output to real-world data. Instead the model behaviour is compared to general observations of different events. For example the behaviour of Epstein's model of civil violence proposes not one, but two models of civil conflict, neither of which are compared to any real-world observed events [55]. Other studies claim to compare to real-world situations, such as the Arab Spring or the London riots, but also do not show how the model behaviour relates to data of those events [103]. Instead these studies highlight some of the general phenomena observed during real-world events, and relate these back to the model behaviour [35].

The only exception to the lack of data comparison so far is the Davies model of the 2011 London riots. Despite having data available on those riots, it is not shown how the model behaviour matches with the number of police and rioters during that period. Instead their model describes a single typical evening during that period, and it is shown how the housing location of arrestants matches with records from the London Metropolitan police service [48].

Additionally many of these models do not consider or largely ignore more than half a century of research into the motivations of individuals to join in acts of collective action such as protests and riots. Even the agent-based models, which describe the behavioural rules of individuals in the agents, do not include or describe concepts like collective identity and efficacy despite overwhelming evidence that these are highly important in determining whether an individual will take action.

The concepts proposed by rational choice theory, critical mass, and the social psychology of protest are general in nature, and therefore apply to most, if not all, situations of civil unrest. Building these into a numerical model would allow to create a model that can describe multiple riot situations. Such a model would then be able to explain different riot situations using a single framework, rather than a specific model for each situation. The Davies model of the London 2011 riots for example was able to compare against data by taking a very specific strategy of using retail sites to predict riot locations [48]. This makes the motivation of the agents very specific, and might not be appropriate in cases where not looting, but car fires are the main phenomenology of the riot, such as the Paris 2005 and Stockholm 2013 riots [114, 170, 171].

Despite 50 years of research into the emergence of collective action and protests, large events of civil unrest like the 2011 Arab Spring and London riots were not anticipated, as shown by the general surprise concerning these events (e.g. [20] and the unpreparedness of local police responses (e.g. [121])). The general (global) response to these events demonstrates that there is not enough knowledge about which, and how, underlying conditions give rise to (the escalation of) civil disturbances and violence. A better understanding of these relationships could potentially aid in the development of measures that can be taken to help detect and address these underlying conditions, and subsequently weaken the motivations for individuals to engage and participate in civil violence.

The lack of understanding between the relationships of certain underlying conditions and the escalation of violence leads to the overarching research question in this work: What are the determining factors that drive riot behaviour ( $Q_0$ )? Besides the probability that a riot will occur, equally important aspects of the characteristics of riot events are the spread of violence, the total activity of the participating individuals, and the duration of unrest. Solely predicting events is not sufficient, as the scale and severity of an event ultimately determine the impact. Furthermore, such predictions do not help in understanding and addressing the underlying causes, and might only postpone the occurrence of violence. Lastly, the ability to predict events of civil violence could also be misused, both to keep populations suppressed, and by exploiting and manipulating such events to force regime changes. In this thesis I therefore specifically focus on how underlying causes and other environmental conditions relate to the escalation of violence, following the assumed start of an event.

To answer the main research question in this study I develop a new numerical model of riots, where the motivation of an individual to join is based on general concepts, such that it has the potential to be used and applied to multiple specific behaviours. In order to leverage the social theories about collective action I adopt an agent-based framework, such that the main findings of the last 50 years of research into the motivations of individuals to join such events can be directly implemented in the behaviour of the agents. Additionally I demonstrate how such a general model can be applied to the specific situation of the London 2011 riots.

The social psychology of protest shows that the collective identity of individuals is a key variable in predicting whether an individual will engage in collective events, including those of civil unrest. It also stipulates that the collective identity is formed

as much prior as during collective actions and protests. Protests preceding a riot could therefore have an important impact on riot behaviour, yet this relationship has not been explored yet, leading to the question of how gatherings prior to outbursts of civil violence determine the probability of a riot ( $Q_1$ ).

Several studies have looked into the effects of the structure of networks on the emergence of collective action. What has received less attention is how the information that is communicated along these networks influences behaviour. Particularly the reliability of information that is communicated about the situations is vital for the police to create an appropriate response to prevent further escalation. Situations like riots are generally very chaotic and dynamic, making it hard to give an accurate assessment and provide detailed information about the state of the riot. I therefore investigate the effect of uncertainty of information about the riot on the police response in the context of the London 2011 riots.

Three interrelated factors that determine the impact of riots are the riot intensity and spread, and the police response. . More intense outbursts of violence might elicit a larger police response to contain and to limit damages. Under certain circumstances, for example if unrest occurs unexpectedly, a local police force might not have the capacity to deliver an appropriate response immediately and will have to rely on aid from police units in surrounding areas. However if a riot spreads to multiple locations, such support may no longer be possible, forcing police officers to rethink their strategy and goals. The London Metropolitan police found themselves in such a situation in 2011 during the first three days, where the main focus was to prevent further spread and contain the violence and aggression rather than apprehending the rioters. Of these three interrelated factors, the spread therefore seems to be particularly important in the strategy that the police needs to employ to limit damages.

In order for violence to spread from one location to another, the individuals in the community in that other location will need to identify or sympathise with the frame or the cause/goal of the riot. For example, there could be a shared sense of deprivation with another group, creating a sense of solidarity and the formation of coalitions between those two groups. The influences of collective identity and the frame of the riot on coalition formation between groups ( $Q_2$ ), facilitating the spread of a riot from one location to another, has not been explored yet within numerical models and is another question that is addressed in this work.

The last question relates to observations of strong relationships between certain

## 1.10 Research Questions and Motivation

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demographic structures and the presence of conflict. Particularly an abundance of young males between the age of 16 and 29, called a youth bulge when 40% of the population falls between these ages, combined with poor socio-economic circumstances seem to lead to situations of unrest [45]. This could be the reason for the 2013 riot of Stockholm, that have been associated with segregation of immigrants. Studying the demography of the main non-European migrant groups in Sweden reveals such a minor youth bulge. Moreover, particularly young immigrants seem to have felt that they had less chances at succeeding in life [170]. Prior to those riots, Stockholm has experienced earlier episodes of civil violence associated with these groups between 2002 and 2009 [114].

The unrest in Sweden associated with immigrant minority groups in certain neighbourhoods leads to the question of how such riots are established as a result of the social structure and spatial dispersion of potential participants in urban environments, and the effect of the demography of these populations ( $Q_3$ ). This question is addressed in the context of the current 'immigration crisis' in Europe. Following the 2011 Arab Spring, the civil war in Syria has led to a significant increase in immigration in Sweden and other European countries. Given the recurrent episodes of violence in Sweden associated with migrant groups, increased levels of immigration could further influence or exacerbate the probability of riots, and potentially lead to similar circumstances in other countries in Europe.

Summarising, the following questions are addressed in this thesis:

$Q_0$ : What are the determining factors that drive riot dynamics?

$Q_1$ : What is the influence of pre-gatherings on riots?

$Q_2$ : How do network properties and (dis)similarities in collective identities between communities facilitate coalition formation and the spread of violence?

$Q_3$ : How are riot dynamics influenced by social, spatial, and demographic structure of potential riot populations?

## 1.11 Thesis Outline

This thesis is divided into seven chapters, including this introduction. The rest of the thesis consists of two chapters that describe the riot data and model, three research chapters, and ends with a discussion.

Chapter 2 describes two sets of data that were obtained from the London Metropolitan Police Service (MPS) about the 2011 London riots, and the 2013 riots of Stockholm, obtained from the Stockholm police. A summary of the general patterns observed in these events is given, as well as a short exploration of what other data sources are used by other models and what potential data can be used in the future. Specifically highlighted are those aspects of the data that have informed and inspired the formulation of the general riot model used in this work.

Chapter 3 describes the basis of my numerical model for riots that I use in the three subsequent research chapters. I explain how the concepts in the model relate to earlier theories of collective action participation, critical mass, and the social psychology of protest.

In Chapter 4, I show how the model can be applied to the 2011 London riots to demonstrate that a general model can capture the behaviour of a specific event. I demonstrate how the output of the model recreates the dominant patterns observed in the data provided by the MPS. Additionally the model is used to infer how protests proceeding riots can produce different behaviour, particularly in total riot activity and riot duration. This chapter also looks into different police responses to those riots and the influence of uncertainty of information that inform the police response. This chapter has also previously been submitted as a paper.

The probability that riots spread to other locations is investigated in Chapter 5. Particularly I look into the influence of collective identities between two different groups to study under which conditions such groups are likely to form coalitions. Another important variable under investigation is the network structure connecting these communities, and the correlation of grievances that these groups might have towards the government.

The last research Chapter 6 looks into the impact of the size, demography, and spatial structure of rioters, in the context of immigration. I investigate how riots are



## 1.11 Thesis Outline

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established through the number of rioters and their spatial dispersement over multiple neighbourhoods within a city, and how the probability of unrest is further influenced by demographic shifts induced by immigration.

Finally this thesis concludes in Chapter 7 with a discussion of the results of this work, and highlights potential future topics for research.

# CHAPTER 2

## Data

### ABSTRACT

The most important way to evaluate mathematical models is by comparison with real world observations, for example in the form of quantitative data. Yet many of the mathematical models that describe civil disturbances lack such comparisons. One of the reasons is that appropriate data is either unavailable for many real world events, or is hard to obtain. This chapter introduces two datasets relating to the riots that took place in London in 2011 and in Stockholm in 2013.

**Author Contributions:** This chapter was written by Jelte Mense, with editorial contributions from Paul Palmer and Matthew Smith.

# 2.1 Introduction

Mathematical models describe the relationships between input and output variables. These models can be used to predict the behaviour or values of output variables by declaring the initial conditions and parameters, and processing them through the mathematical formulae that make up the model. This method can also be used to forecast and explore possible scenarios, by using alternate initial conditions that do not represent the current situation, but might occur in the future. For example using simple physical laws, the final velocity of an object hitting the ground can be calculated if given the height from which the object is dropped, under the assumption that there is no drag resistance. In the same way theories about human behaviour can be implemented in mathematical models, to find out under which circumstances individuals are more likely to engage in collective action (e.g. [142]).

When trying to predict outcomes or exploring new theories about the relationships between initial conditions and final states, the evaluation of model predictions with real world observations is one, if not of the most, important way in which such models can be (in)validated. If the model cannot recreate patterns for known conditions, there is no guarantee that the model predictions that are generated for different (future) scenarios will be more accurate. Comparisons of model predictions with relevant data is the key mechanism by which competing theories can be eliminated and scientific progress can be made.

Yet the behaviour from numerical models of civil violence are rarely directly compared with quantitative data on the specific phenomena they are aiming to reproduce. Particularly the subcategory of agent-based models (ABM) generally do not validate model output by evaluating against quantitative data from real events (e.g. [55, 129, 198]). Next to this work the Davies model is the only other study involving agent-based models that considers data. However instead of comparing model output to riot activity, which they have available in the form of the number of hourly offenders during the London riots, they instead show how their model predicts the home location of the offenders during the London riots during a ‘typical evening of the London riots’ [48].

Additionally many models do not show the basic characteristics of the model, e.g. the number of rioters and police officers for each iteration, but instead only present relative differences in model behaviour as results [24, 103, 104]. Such results

are not transparent without supplying at least a single reference point or control case, such that readers can obtain a basic impression of the general model characteristics. Without a demonstration of some standard or reference model run, there is no way for a reader to be sure that these models actually exhibit behaviour that is anything like a riot.

Studies that use approaches other than an ABM offer more comparison of model output and real world observations. The general occurrence of conflict and the diffusion of violence in riots has for example been successfully modelled using statistical models (e.g. [17, 31, 131]). However these models are different in nature, as they do not causally or mechanistically describe how variables relate to each other. They are suitable for discovering potential relationships in the events that they analyse, but due to the lack of tractability of relationships between variables they are less applicable for forecasting and scenario building outside those events.

A direct comparison with quantitative data is not always necessary. A model that explores the physical mechanisms in a phenomenological perspective is the work of Brummit, where the diffusion of violence is simplified to two qualitative mechanisms of spread: 1) the infection of violence from one location A to a neighbouring location B, and 2) violence spreading from A to a third location C through B, where B then does not experience any outbursts of violence, and A and C are only connected to B and not to each other [35]. The phenomenology that the model targets is clearly defined, and it is demonstrated under which conditions their model exhibits either of the two behaviours, followed by how these simplified patterns occurred in the 2011 Arab spring.

This chapter describes two new datasets related to the 2011 London riots and the 2013 Stockholm riots. The next sections give a short overview of the events of these riots, and describe the datasets along with analyses. The chapter concludes with a short discussion of different indicators of riot severity and potential future data sources. The data featured in this chapter inspired the model design, which is described in Chapter 3, and the output of the model is compared to London 2011 data in Chapter 4.

## 2.2 The 2011 England Riots

The riots in England in 2011 started on the 6th of August in London, at the Tottenham police station [121]. Over the next days riots broke out in surrounding boroughs in London, and also major cities in the UK such as Birmingham and Manchester. By the fourth day over 16,000 police officers were deployed in London to control the situation, and by the fifth day most of the riot activity had subsided. The main offences during the London riots were burglary and violent disorder, together accounting for 70% of the total offences that appeared in court [121, 161].

The event commonly cited as the event leading up to the 2011 London riots is the death of Mark Duggan on August 4th 2011, two days before the start of the riot. Believed to be carrying a firearm, the MPS (London Metropolitan Police Service) made an attempt to arrest Mark Duggan whilst he was in a taxi. He managed to escape and whilst fleeing was shot in the back by an MPS officer. Perceived as an act of unnecessary police violence coupled with unclear communication about the circumstances surrounding Mark Duggan's death, a march in protest of police violence held on the 6th ended at the local police station in Tottenham, which transitioned into the start of the riots [121, 161].

When the protest march arrived at the station, the family of Mark Duggan entered the police station to talk to the local head of the police. After leaving the station, the family expressed the wish see a more senior officer of the police. This request was not anticipated and not expressed prior to arriving at the police station, and could thus not immediately be resolved. While waiting on a more senior police officer to arrive, eventually around 8 o'clock in the evening, protesters began to hurl projectiles at the present police officers and aggression spiralled out of control starting the riots [121].

Over the next couple of days the violence spread to multiple boroughs within London, and also to other large cities in the UK including Birmingham and Manchester. The MPS in London faced great challenges having to contain and control violence against police officers, arson and opportunistic looting. The rapid spread caused a shortage of police resources during the first days of riot riots, and the total economic damages have estimated to be in excess of 250 million pounds [18, 121, 161].

### 2.2.1 The Role of Social Media in the London Riots

The London riots were among one of the first events where the impact of social media was explored as one of the possible reasons for why violence spread so quickly to various locations over London [121]. Not only was this opportunity unprecedented for those seeking to cause disruption, it was also a new factor that the police had to take into account during the London riots.

The role of social media during the London riots has thus received much attention, and most of the studies involving the London riots and social media focus on Twitter, following hashtags and mapping the topology of the network (e.g. [22]). These studies are able to find, for example, the major influencers whose messages have had the most impact during this period. However newspapers report that unlike the Arab Spring in that same year, Twitter only played a minor role in facilitating the riots. Instead the messaging service BlackBerry Messenger seems to have been the dominant way of communicating information between individuals during the riots [15, 75, 121].

In 2011 this messaging service was still exclusive to BlackBerry phones, and due to the ease of the service and the low price of such phones it became a very popular and widely adopted during that period [15].

Specifically the broadcast function featured on these phones, which enables the user to send and forward messages to multiple contacts simultaneously, caused information about the riots to spread quickly. Additionally, unlike Twitter, such messages are private and not traceable by the police.

Despite the inability to trace such messages the MPS has committed to developing more intelligence methods for researching social media. Although BBM was the dominant social network during this period, the MPS also had very limited technological ability to detect and trace other messages on more public social media networks such as Facebook and Twitter, relying instead on reports and phone calls from individuals who were receiving them [121].

### 2.2.2 London Riots Data

The data on the London riots from the MPS was obtained through a freedom of information request initiated by me and my supervisors [122]. The available data consists of three categories: the number of emergency calls made to the MPS, the

## 2.2 The 2011 England Riots

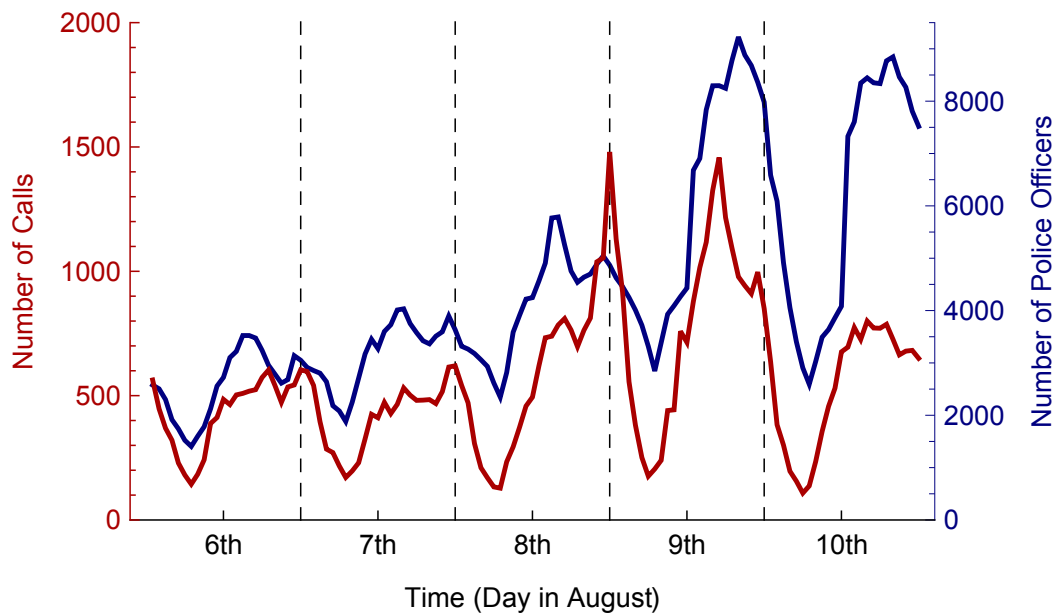
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number of active police officers, and the number of arrests. All of these are available for each borough in London for each hour during the period between 6-10 August, 2011. The number of calls are further divided into four different urgency categories: the two highest (I & S) values have a target response time of 15 to 60 minutes and the two lowest values are dealt with by appointment, or are referred to another source or do not need a response. The number of hourly calls are filtered for duplicate calls. The MPS noted that for the number of active police officers in each borough there was no guarantee that those police officers were actually deployed to address issues within that same borough. Next to the London boroughs the dataset on the number of active police officers also includes teams that are not specifically stationed in any particular borough. The arrest data consist of all arrests and not just those related to the riots.

Figure 2.1 shows the caller activity and the number of active police officers for all boroughs during the London riots. The total number of daily calls per day increases slightly from the first to the second day, then greatly increases on the third, increases further on the fourth, and drops dramatically on the fifth and last day of the riot. The start of the riots can be seen on 6 August by the increase in the late evening creating a second peak that day in the caller activity. This same pattern where there is a rise in the volume of calls in the late evening can be seen throughout the riot period. Generally the peak activity in the evening is higher than during the day, except on 9 August, where the peak activity in the afternoon is roughly equal to the peak activity of the night before.

The number of active police officers increases during the first four days of the riots and slightly decreases on the fifth. The daily maximum increases in the first four days, and follows an exponential shape. The minimum amount of daily police increases linearly in the first four days. Like the caller activity, the start of the riots can be observed on the first day as the second peak on 6th of August in the evening. Generally the police and caller activity for each day is characterised by two peaks, one in the late afternoon, and one later in the evening. There is a general diurnal cycle, where activity between midnight and early morning is significantly less than during the day. The daily minimum number of police officers occurs every day at 6 AM in the morning. The peak activity typically happens around 3 o'clock in the afternoon, which is likely related to schools finishing and police shifts overlapping between the day and evening shifts. Over the whole period the peak number of police officers more than doubled from less than 4,000 on August 6, to more than 9,000 on August 9.

Figure 2.2 shows the hourly number of urgent calls and arrests during the



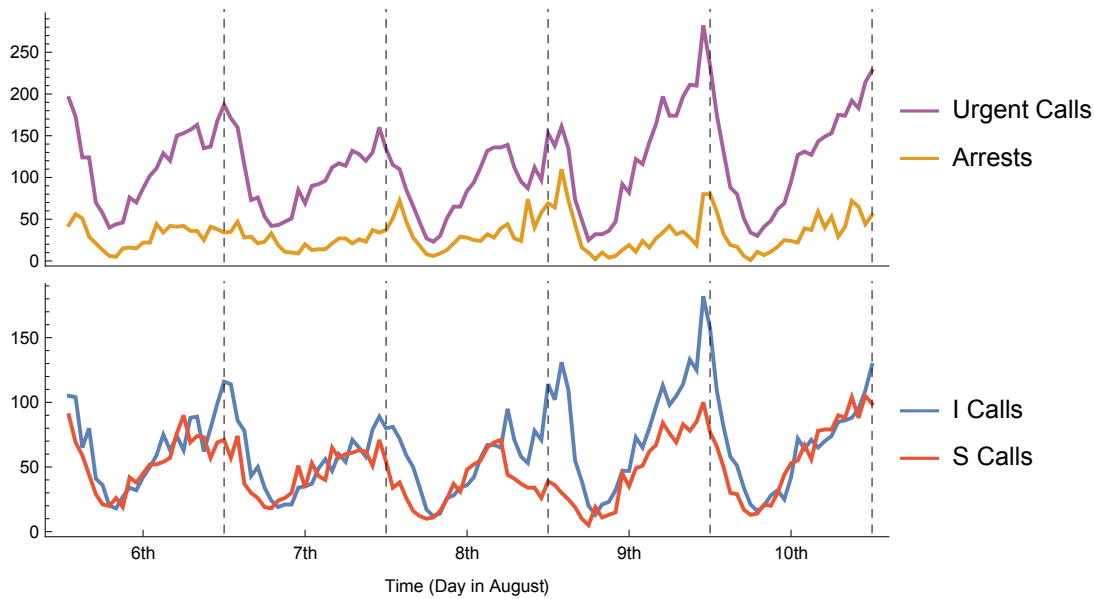
**Figure 2.1: Number of calls and active police officers during the 2011 London riots.** The hourly number of incoming emergency calls to the MPS is shown in red on the left vertical axis, the number of active police officers is shown in blue on the right vertical axis. The ticks on the horizontal axis are at midday, the dashed vertical lines denote midnight.

London riots. It also shows a breakdown of the urgent calls into the two ‘I’ and ‘S’ response categories, requiring a response of 15 and 60 minutes. The start of the London riots can hardly be observed from the number of arrests. There is a small peak after midnight, but this could also be described as noise. On the following days however, there are clear peaks in the number of hourly arrests after and around midnight relating to the riot activity.

The urgent calls made to the MPS show the same diurnal cycle as the total number of calls. Peaks in daily activity generally occur around midnight, and decrease slightly in intensity during the first three days, with a big increase on the fourth day of the riots on August 9th. The number of urgent calls show a slightly different pattern as the total volume of incoming calls to the MPS increased during the first three days and remained stable on the fourth. The fact that fewer calls are categorised as urgent is striking given the increase in riot activity during that period. The increase on the fourth day can be potentially explained by the sharp increase of the number of police officers on the fourth day, that might have allowed to classify more calls into the urgent calls categories, because more resources were available to respond within the assigned target response times.



## 2.2 The 2011 England Riots



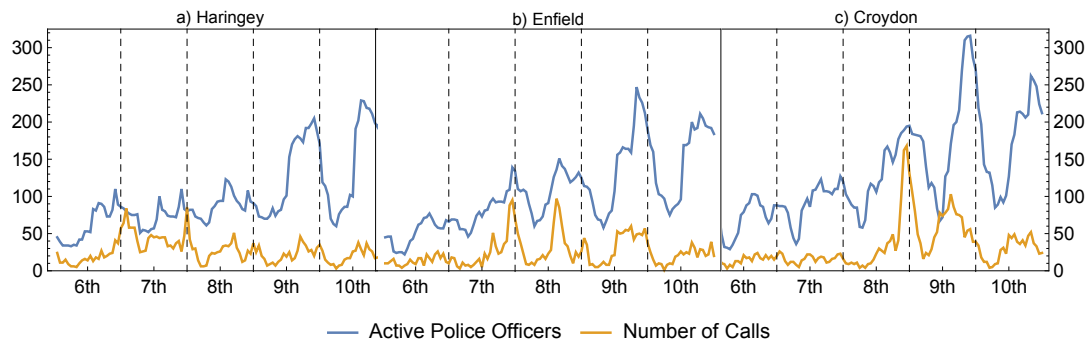
**Figure 2.2: Urgent calls, arrests and calls breakdown during the 2011 London riots.** The upper panel shows the hourly number of urgent calls in purple (I and S categories) and the number of arrests in yellow. The bottom pane shows the breakdown of the urgent calls into the separate I and S categories in blue and red. I calls have a response time of 15 minutes, S calls have a response time of 60 minutes. The dashed vertical lines denote midnight.

The urgent calls consist of two response categories (I and S) that have target police response times of 15 and 60 minutes. The number of calls within these two categories are generally at a similar level during the day, but during the night the number of I calls that fall under the immediate response category are generally higher. On the fourth day also during the day more of the incoming calls are assigned an immediate response. This pattern could potentially be explained by the arrival of extra police forces in London, that allowed the MPS to assign more calls to the highest urgency category.

The number of hourly arrests could potentially have a lag dependent on when the incidents are reported. For example after an arrest there is a travel time between making the arrest and arriving at the police station, and if incidents are only reported once officers return to the police station there would be delay between the time of arrest and the time the arrest is recorded. To check for such a possible lag time I performed a lagged autocorrelation analysis to see if adding a lag in both directions would increase correlation with the caller activity and the number of active police officers. Adding a lag to either the arrests, the caller activity, or the number of active

police officers did not improve correlation, indicating that there is possibly no such lag present in the data.

Figure 2.3 shows the caller and police activity in three different boroughs in London of Haringey, Enfield, and Croydon (see Appendix 8.1 for a map of London showing the locations of these boroughs). The riots originally started in Haringey on August 6, spread to Enfield and other boroughs on the next day, and Croydon experienced rioting activity from the 8th of August. The number of calls in these boroughs reveal an important observation: opposite to Figure 2.1, the number of calls within these boroughs generally decrease over time, whereas the number of calls for the whole of London initially increase, and only decrease on the last day.



**Figure 2.3: Number of hourly calls and active police officers in Haringey, Enfield and Croydon during the London riots.** The number of active police officers is shown in blue, the number of incoming emergency calls is shown in yellow. The Haringey borough in London is shown on the left, Enfield in the middle, and Croydon on the right. The dashed vertical lines denote midnight.

The opposite trends of the global and the local caller activity is very important for describing the London riots in a numerical model. When trying to capture the behaviour of the riots in the individual boroughs in London, the model should reproduce the locally decreasing activity, instead of the increasing global behaviour. The difference between the locally decreasing but globally increasing number of calls can be explained by the riots spreading at a faster rate than the decrease in number of calls at the borough level.

The number of active police officers in Haringey follows a very similar shape to the total number of police officers for the whole of London. In Enfield and Croydon, there are larger peaks on 9 August in the evening, with 1.5 times as many police officers present in Croydon than in Haringey. There are also signs of the MPS

## 2.2 The 2011 England Riots

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anticipating unrest, as the number of police officers in Croydon on 8 August was already greatly increasing before the spike in the number of incoming calls occurred shortly before midnight.

### 2.2.3 Other Data from the London Riots

The London riots are a comparatively rich source of data on riots compared to other events. The reports ‘4 days in August’ from the MPS and ‘5 days in August’ from the independent Riots, Communities, and Victims panel, established by the UK government, give a very detailed account of the events that transpired before and during the riots [121, 161]. Additionally these reports feature a wealth of data in the form of charts about various subjects, for example the number of reported crimes in each area. The data on which these charts are based have since been made publically available by the Ministry of Justice (MoJ), and contains detailed information on the general composition of arrestants and the crimes they were apprehended for (e.g. Tables 2.1 and 2.2) [127, 164].

**Table 2.1: Ethnicities of individuals that were brought before court after the 2011 riots in England.** *Adapted from [127].*

	Appeared in court
<b>Ethnicity</b>	
White	1,098
Black	1,051
Asian	178
Mixed	321
Other	60
Not stated /recorded	395
Total	3,103

The Guardian newspaper in combination with the London School of Economics released a series of articles (e.g. [159]) and a report called ‘Reading the riots’. This report mostly leans on 270 in-depth interviews with participants of the London riots, with the aim to find who they were and what motivated them. Additionally the Guardian also obtained a dataset consisting of ‘tweets’ (public Twitter messages) during the London riots, that was analysed by staff of Manchester University. Lastly

**Table 2.2: Number of individuals appeared in court per age group.** *Adapted from [127].*

Appeared in court	
Age Group	
10 to 17	760
18 to 20	658
21 to 24	546
25 to 30	343
31 to 34	124
35 to 39	66
40+	149

their analyses also rely on the MoJ dataset of arrest information [112].

A team of researchers at University College London obtained a dataset on the times and locations of committed offenses, allowing them to focus on the spatiotemporal patterns of diffusion of riot behaviour during the London riots [16, 17]. The dataset also contains the age and home locations of the apprehended offenders, such that they were able to show that the likelihood of distance travelled between home and offending locations falls off exponentially with distance, and that individuals were thus more likely to stay within their own neighbourhoods [18]. In a follow-up study they then show how their agent-based riot model predicts the home location of offenders during the London riots [48].

**Table 2.3: Summary of available quantitative data on the London riots from academic studies, in addition to reports and data from the UK government [121, 127, 161].**

Source Name	Data	Reference
Metropolitan Police Service	Number of calls	[122]
	Number of arrests	
	Number of police officers	
London School of Economics & The Guardian & The University of Manchester	Interviews	[112]
	Twitter Database	
University College London	Offense time & locations	[16, 17]
	Offender age and home location	[18, 48]
	Number of daily police officers	[48]

## 2.3 The 2013 Stockholm Riots

The Stockholm riots of 2013, like the England riots, were preceded by an incident on 13 May 2013 during which a man was fatally shot by the police. Many riots in the last decade have started with events of (perceived) police violence, as discussed in Section 1.8. Reports came in of a confused elderly foreign male with machetes roaming around in Husby in Stockholm, Sweden. Responding to the reports the police found and confronted the man in his home, where after escalation they fatally shot him [187].

Similar to the London riots the circumstances regarding the death of the man were not clearly communicated. The Stockholm police reported that an ambulance took the man to the hospital after the incident, where he was pronounced dead. The local political youth group Megafonen however stated that they never saw an ambulance, and that instead a hearse turned up in the middle of the night to take the body away [197]. The police statement regarding the death of the elderly man has also been altered since the different claims [197].

In protest of the shooting the local political group Megafonen organised a protest march [170]. Later on the 19th of May riots broke out in Husby, Stockholm, where the incident occurred [219]. Eventually the violence spread to other areas of Stockholm and other cities in Sweden [191].

### 2.3.1 Stockholm Riots Data

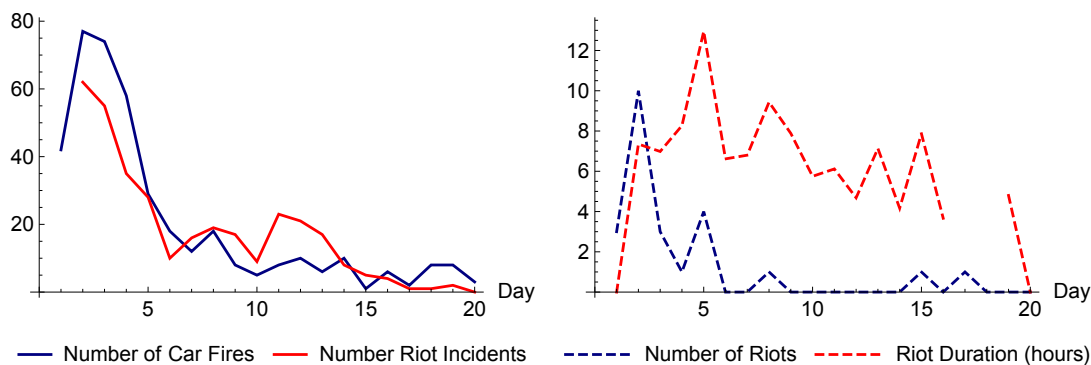
There is less information available regarding these riots compared to the London riots, especially in English. Following an enquiry to the Stockholm police, I received data on the Stockholm 2013 riots. The data consists of the number of daily (nightly) incidents between 22 May and 10 June 2013, the number of individual daily riots, and where available also the start and end times of unrest for each day. The data also includes a detailed list of the different type of incidents that were recorded each day, such as the number of car and school fires. Data on the police response during the Stockholm riots was not provided as the Stockholm police considered it to be confidential.

The main phenomenology of the Stockholm riots were car fires, as opposed to the London riots where the opportunistic looting was the dominant behaviour [121, 219]. Rioters in Stockholm also targeted schools, threw projectiles at policemen and police

## 2.3 The 2013 Stockholm Riots

cars, and vandalised police stations.

Figure 2.4 shows that the number of nightly car fires almost doubles from the first to the second day, and then slowly decreases. The number of riot incidents follows the same pattern but shows an increase in activity on day 5 and day 10. On some days the number of riot incidents is lower than the number of car fires, which is likely due several car fires being grouped together and are categorized by the Stockholm police as a single riot incident.



**Figure 2.4: Number of Car fires, Riot Incidents, Riots and Riot duration during the 2013 Stockholm Riots.** *Left shows the number of daily car fires and riot incidents in blue and red. Right shows the number of riots and the riot duration in hours in dashed blue and red. The riot duration is not available in the data for every day.*

The number of riots follows the same pattern as the number of car fires; there is a sharp increase from 3 to 10 riots from the first to the second day, and then the number of riots generally decreases. Disregarding the peak in the number of riots on day 2, only on day 5 do the number of riots peak above the initial number of riots on the first day. The riot duration increases at first, peaking on the fifth day together with the number of riots, and likewise decreases afterwards. There seems to be no clear relation between the number of riots and the total riot duration.

Figure 2.5 shows the riot start and end times. The riots in Stockholm generally started between 6 and 8 o'clock in the evening during the first half of the riots, but started later during the second half. The riots mostly ended between 2 and 4 o'clock at night, with the fifth day of rioting being an exception and riot activity continuing until 6 o'clock in the morning. The shorter riot duration shown in Figure 2.4 towards the end of the riots is mainly driven by the later starting times of the riots.



**Figure 2.5: Riot start and end times in the 2013 Stockholm riots.** *The start times of the riots for every day is shown in cyan, the end times of the riot in purple. The end times of the riots are not available for every day of the riots.*

There are several key differences between the London and Stockholm riots. The main difference is the total riot duration; the London riots lasted between four and five days whereas the unrest in Stockholm continued for nearly 3 weeks. The rioting behaviour differed greatly between the two locations, Stockholm was heavily affected by car fires and vandalism of several types of public property (e.g. police stations and schools), whereas during the London riots mainly private properties (shops etc.) were targeted for opportunistic looting.

The crowds that participated in the riots were also different. In London the people that were arrested reflect a wide range of backgrounds, with roughly equal percentages being of black or white ethnicities (see Table 2.1)[127], whereas the Stockholm riots were mainly attributed to those with an immigrant background [84, 191]. Following the riots both locations had a response from the general public, in London the hashtag ‘#Riotcleanup’ was initiated on Twitter to organise volunteers to clear debris [22]). The response in Stockholm mainly consisted of nightly patrols to protect public properties like schools. There are different reports about who participated in these groups, as some news articles describe the patrols consisting of worried parents [148], whereas other reports claim that the patrols consisted of members of right-wing extremist groups [153].



## 2.4 Beyond the Number of Calls and Car Fires

Different methods have been proposed to measure the severity of a riot, e.g. [117, 180, 210]. These metrics are designed to compare events with each other, but do not consider how individual riots change over time, such as how the severity builds up from the beginning towards the end. Instead the proposed severity scales try to capture the ‘total’ riot activity over the whole period once disturbances have stopped. Such an approach however cannot address for example the important difference between the London and Stockholm riots, short and intense versus prolonged and more passive, as the dynamics are compounded into a single number. Although it would be interesting to see how an individual event scores per day or per hour on any of the proposed severity indexes as it progresses, other and perhaps more direct metrics could be used to describe the evolving activity of disturbances.

In the previous sections the number of calls, car fires, and arrests are all indicators of how the riot activity varies throughout the event. But one problem with the number of calls in the data set on the London riots is that the calls do not uniquely relate to riot activity. I therefore compare the call records with police reports on when riots started and ended in order to relate increases in the volume of calls to riot activity. The number of calls is dependent on the capacity of emergency services to take and log relevant incoming calls. Like the number of calls, the number of arrests is a general metric of activity and does apply to most riot situations, as it is dependent on the available resources and focus of the police. During the first days of the London riots the MPS was forced to focus their efforts on containing the riots rather than arresting those committing offenses [121]. Only later when enough police officers became available were they able to start arresting individuals, giving a skewed impression of riot activity before that period. The number of car fires is another measure that can be used as a proxy of riot activity, but only applies to certain riots and can therefore not be used as a general comparison between different events.

The number of calls, car fires, and arrests are the results of the interaction between rioters and police officers. Larger crowds are harder for the police to deal with, and will consequently result in less arrests and more car fires and emergency calls. Beyond the number of rioters and police officers there are also qualitative factors that decide the outcomes of riots, such as the aggressiveness of the participants, and the level of coordination of the police response. The total crowd aggressiveness is a product of crowd size and the average ferocity of an individual. Smaller gatherings with highly

aggressive individuals can result in a similar level of riot activity as larger and more passive crowds. The ferocity of individuals is hard to objectively measure, but the crowd size can be obtained in a number of ways, such as indications from police and newspapers. Using for example the number of car fires as an indication of the total crowd activity, the average aggressiveness of the individuals can be approximated by dividing the riot activity with estimations of the riot size.

Another source of data used in other studies is the approximate location of individuals using cellular towers and mobile phones. Previous studies have used such data to track the movement of individuals to explain spread of disease [213]. Such methods could also be used to more accurately measure the number of individuals present at a riot [30], rather than use the number of calls which mainly expresses the total riot activity. While it would be impossible to differentiate between bystanders and active rioters, such data combined with precise data on police movement could reveal gaps in strategy [51].



# CHAPTER 3

## A New Riot Model

### ABSTRACT

To study riots I develop a new mechanistic agent-based model. The motivation of the agents to join riots is informed by social theory. Additionally the processes of the agents joining and leaving the riots, and the following police response, are expressed in general terms that apply to multiple riot situations, rather than being specific to a single riot. This chapter describes the model and explains the motivations behind the model framework design. I also describe the metrics that are used in the subsequent research chapters to measure the characteristics of a riot (e.g. duration, intensity).

**Author Contributions:** This chapter was written by Jelte Mense, with suggested edits from Paul Palmer and Matthew Smith.

# 3.1 Introduction

This chapter introduces a new agent-based model that is used in the three subsequent research chapters. Specifically I describe the ‘core’ model, as each of the following chapters use slight variations of the same model in order to address specific research questions. This chapter also discusses the motivations behind the model design, as the individual chapters only include a summarised model description.

Previous attempts to model riot behaviour have included methods of differential equations, agent-based models, grid-based models, and statistical methods [16, 25, 31, 55]. In this work I have chosen to use agent-based model over other methods. In agent-based modelling the model behaviour is obtained as a result of the interactions of so called ‘agents’ with each other and their environment [66, 77]. Each agent is described along with a behavioural algorithm, that drives its decisions. The agents in my model represent individuals that would consider joining a riot. The main reason to use this approach is that the theories about why individuals participate in collective action can be directly implemented into the agents in the model. Before arriving at an agent-based model, I have also attempted to model the behaviour within the riots using differential equations, which is described in greater detail in Section 3.13.

The motivation to introduce a new model framework for describing riots rather than adopt an existing one is based on three reasons. First, the existing models, particularly those that are agent-based, largely ignore the contributions of social theory about why individuals would join such events when investigating riot behaviour. Second, until now none of the agent-based models have demonstrated how their model behaviour compares to actual observations of riot behaviour from real events. Third, there is a strong divide between models that target general phenomena, and those that aim for specific events, opening the way for a new ‘hybrid’ approach as presented in this chapter. I elaborate below on each of these reasons.

One example of a model that largely ignores theories about the motivations of individuals to join in (rebellious) collective actions is Epstein’s model of civil violence [55]. It is a good demonstration of how simple and understandable rules in an agent-based model can produce the complex dynamics of human behaviour. However Epstein does not explain how the motivations of the agents to join in rebellious action relate to more than fifty years of contributions from social theory on the same subject, which raises the question about how useful or applicable the model actually is to real

situations of civil violence. Likewise for example, predictions and policy suggestions from a climate model that ignores theories and knowledge about the main chemical processes in the atmosphere should be regarded with great scrutiny.

The problem is not necessarily in Epstein's work itself, as he does not make claims that riots should be handled in a certain way or attempts to predict real-world behaviour. Also the introduction of new mechanisms that have not been suggested or investigated by other disciplines is not an issue, as such concepts can sometimes lead to new discoveries and force researchers to develop new theories.

Rather the problem instead is with other researchers that base their model on Epstein's work, present it as a true model of riot behaviour, and start making policy suggestions or claim they have found the answer as to how social media for example influences riot dynamics (e.g. [105, 214]). Also due to the ambiguity of Epstein's research goal and model description it has been applied to both riots [198] and revolutions [129], despite such events having considerably different behaviours and targets due to other motivations and objectives (see Section 1.2). My model incorporates some of the concepts proposed by Epstein, but I explicitly relate them to findings of social theory to justify their use.

The second reason for building a new model of riots is that previous attempts of modelling riots have mainly presented metrics of riot outcomes associated with their model, such as the aggregate severity or total number of incidents, but do not show the intermediate behaviour of how the riot evolves with time (e.g. [24, 48, 103, 104]). The metrics on the model output are then compared to each other at different parameter settings, without showing how the model behaves at a single parameter setting. It is therefore hard to assess whether these models actually exhibit dynamics that are consistent with observations from real events, leading to my decision to develop a new model rather than build upon these existing models.

The third reason to build a new model for riots is the two approaches of generality versus specificity. The concepts and theories proposed by the theory of collective action and the social psychology of protest are general in nature, and theoretically apply to a wide range of situations of collective violence. Since these theories have been built by studying many events, it must therefore be possible to create a numerical model with these theories that can describe various behaviours observed from different events using the same behavioural rules. The different behaviours are then driven by alternate parameter settings or different initial

### 3.1 Introduction

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conditions, but by the same general behavioural rules.

The numerical models that describe specific events have taken another approach instead. Such models are heavily tailored to these events, to the extent that these models no longer are able to describe any other behaviour. For example in the Davies model of the 2011 London riots the riot locations are based on the attractiveness of retail sites, which only applies to looting [48]. Such a model can then not be used to describe the Stockholm 2013 or Paris 2005 riots, where car burnings were the main phenomena [170, 171]. It has not been shown yet that a model based on general motivations for joining riots can exhibit the behaviour of a single particular event.

The model described in this chapter remedies the problems discussed above, by explicitly stating how the concepts in the model relate back to important findings from social theory. Additionally I describe the motivation of the agents to join the riots in general terms, such that it does not uniquely apply to one particular riot, and theoretically could be used to describe multiple riot situations. Lastly I also demonstrate how such a general model can be applied to the specific situation of the London 2011 riots in Chapter 4.

The Sections 3.2 to 3.8 introduce the core model, after which I outline the key differences to the core model for the subsequent research chapters in Section 3.9. Section 3.10 specifies the metrics that I use to compare the model behaviour at different parameter settings. The reasons for why arrests were left out of the model is discussed in Section 3.11, followed by a robustness analysis of the model regarding time resolution and updating mechanisms in Section 3.12. The last Section 3.13 describes other efforts to create a model using differential equations.

## 3.2 A New Riot Model

To answer my research questions I develop a simple and new general mechanistic agent-based model. In agent-based modelling so-called agents are entities who act by predefined behavioural rules. The model behaviour is obtained as a result of interactions between multiple agents and their environment. In my model the agents represent potential individual rioters that can start, join, and leave riots. Additionally there is a separate singular entity described in the model that represents and regulates the police response, expressed as the number of police officers. After a riot has started, agents can join and leave riots in each subsequent iteration. In the same iteration the police responds to the riot, by changing the number of active police officers.

The model that I use is mechanistic, in the sense that the goal is to describe processes in the model that are representative of real world processes. In the biological sciences such models are known as process-based models [36]. As such, the processes in my model are designed to describe (theoretical) causal relationships between input and output variables, rather than abstract and dimensionless relationships that are (solely) based on data patterns or designed to give a best fit with data. I define these causal processes in the model by drawing on contributions from social theory, such as theories of collective action, critical mass, and the social psychology of protest. The outputs of these processes can serve as inputs for other processes, coupling different mechanisms in the model. By describing the model as a system of coupled causal relationships, the theoretical importance of each process can be determined by assessing the sensitivity to that process in the model, and gain a more systematic understanding.

As there are still many parts of human behaviour and collective action that are not fully understood, it is not possible to create a ‘complete’ mechanistic model of civil violence, unlike some models of the natural sciences that are supplemented by centuries of research. The processes in my model are based on various contributions from social theory, which has involved the study of collective actions like protests and riots for at least the past 50 years (e.g. [108, 142]). Although there is evidence that certain aspects of human behaviour are subject to mathematical laws (e.g. [87]), the contributions from social theory mainly consist of qualitative concepts and relationships. The social psychology of protest for example, describe different qualitative concepts that influence the motivation and decision to join in collective action, but does not give quantitative relationships that can readily be implemented



### 3.2 A New Riot Model

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into a mathematical model. In this work I therefore have to make various assumptions and propositions about the mathematical form and strengths of these relationships. However, the use of the word mechanistic in this thesis relates to the underlying philosophy of the model design; to build the model out of coupled processes that should be representative of real-world processes, by integrating various contributions from social theory about human behaviour and (violent) collective action.

My aim is to use the model to describe the different dynamics that take place in a single riot event. Other models have been used to study the frequency with which such events occur (e.g. [31, 100]) and the spatiotemporal spread of events (e.g. [16, 131]). These studies address the when and where questions related to riots, and this model focuses on the the dynamics and characteristics of these single events, such as the intensity and duration, and the interactions between rioters and police.

Specifically my model describes a fixed number of riot locations, as opposed to a grid or other geometric space on which rioters and police officers can move around freely (e.g. [55, 198]). Events of civil disobedience seem to revolve around (locally) well-know public spaces that can support large gatherings. Some examples are the riots in the Schilderswijk in The Hague in the Netherlands in 2015, which took place in and around the Hobbemaplein (square) and the local police station [50, 133, 207]. An important place in the first and second Egyptian revolution in 2011 and 2013 was Tahrir square in Cairo [201], and the riots in Istanbul started after clashes between protesters and police in the local Taksim Gezi park and Taksim square [203, 204]. Also in the 2011 London riots the majority of disorder in the boroughs was centered around similar key locations (see Appendix 8.2) [121]. To recreate this behaviour I limit the locations where agents can riot, representing these places as an abstract space for gathering rather than allow the agents to physically move around.

The basic attributes of the agents are a hardship level  $H$ , an age  $A$ , and a contact network allowing them to communicate and transfer knowledge about the riot to other agents. These attributes are further explained in the following Sections 3.3, 3.4, and 3.5. After the riot starts the agents can decide to join or leave a riot each iteration, followed by a reaction in the police response for the new number of rioters. Section 3.6 specifies the mechanisms of how agents join and leave riots, followed by a description of how the agents start riots in Section 3.7. The model description concludes with a description of the police response in Section 3.8. These sections describe multiple parameters, of which the specific values are further detailed in the relevant research chapters where the model is used to answer the research questions.

### 3.3 Hardship and Riot Frame

Each agent is assigned an individual *hardship* level  $H$  at the start of the model. This concept of hardship has first been proposed by Epstein [55], and has since been used to describe the primary motivator for joining riots in agent-based models of civil conflict (e.g. [48, 129, 198]). In Epstein’s model of civil violence it represents the (perceived) hardship of agents, such as economic deprivation.

The theories from the social psychology of protest stipulate that objective or perceived and relative deprivation (i.e. hardship) is not sufficient for explaining the participation in rebellious collective action [92, 184, 221]. Instead, emotions derived from such perceptions are what drives individuals to join protests. Epstein (independently) makes a similar claim in his model by describing the *grief*  $G$  of agents.

The grief  $G$  of agents in Epstein’s model is produced by multiplying the hardship  $H$ , given by a uniform distribution between 0 and 1, of an agent with a globally, i.e. shared by all agents, perceived *government legitimacy*  $L$  [55]. The argument that Epstein proposes is that only when governments are perceived as illegitimate that hardships produce emotions of grief in individuals. Epstein proposes the following relationship between hardship  $H$ , government legitimacy  $L$ , and grief  $G$ :

$$G = H(1 - L), \quad (3.1)$$

such that equal amounts of hardship result in more emotions of grief when the (perceived) legitimacy of a government is low [55].

Epstein’s model describes a rebellion, but also interchangeably uses the terms of riots and revolutions to describe the targeted model behaviour. The same model has been applied by other researchers to both riots (e.g. [198]) and revolutions (e.g. [129]). Although there is some overlap in behaviours from these different forms of civil violence, there are considerable differences between riots and rebellions or revolutions, as discussed in Section 1.2.

In this work I specifically focus on riots. In riots there is less focus on the government than in rebellions, as the targets of aggression are not specifically related to government buildings [115]. I therefore only consider the emotions (i.e. grief) of the agents that are derived from possible strife and hardships, and do not include the concept of government legitimacy proposed by Epstein [55]. Moreover emotions

### 3.3 Hardship and Riot Frame

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derived from (group-related) strife are better predictors of collective action than objectively measurable hardships such as deprivation [92, 184, 221]. For consistency I denote these emotions by  $H$ , describing the grief or (emotions derived from) hardships of the agents.

In previous studies hardship has been described as a single number between 0 and 1 [48, 55, 129, 198]. I propose a natural extension to expand the hardship into multiple orthogonal non-negative dimensions, such that each dimension represents a different issue about which the agent can be aggrieved. The agent hardship is normalised such that each point lies within the positive quadrant of a unit  $n$ -sphere:

$$\sum_i^D H_i^2 \leq 1 \quad \forall H_i \geq 0.$$

In the simplest case, using only a single dimension, this system reverts to the description of hardship as a single number between 0 and 1. If the number of dimensions  $D$  is more than 1 the points within this  $n$ -sphere can be generated by spherical coordinates, using a radius  $r$  and  $D - 1$  angles.

The main reason for extending hardship to multiple dimensions is to describe differences in (average) hardship between different communities. This enables me to use the model to study how the overlap of different grievances, or reasons and causes of grief, facilitates coalition forming, i.e. the spread of violence from one community or location to another. This is the main topic of Chapter 5.

Following previous studies I use a random uniform distribution ( $U(0,1)$ ) to generate the radii and angles [55, 198]. Other studies have used sigmoid (logistic) shapes to distribute hardships in agents [129], or deprivation data of the specific location under investigation [48]. A discussion of alternative, and potentially more appropriate, hardship distribution shapes is given in Section 7.3.4 in the final discussion in Chapter 7.

#### 3.3.1 Riot Frame

In some cases riots can be traced back to a single event, a so-called riot *trigger*. For example in the London riots the death of Mark Duggan [161], and likewise the death of an elderly man in the 2013 Stockholm riots [170] are commonly perceived as the starting point for the unrest. The way in which these trigger events are presented (e.g.

by the media or by social movements) and are interpreted by individuals creates the riot *frame* [221], i.e. what the population perceives to be the goal and cause of the protest and violence.

Such riot frames have not been included in previous numerical models of riots. They are very important however, one of the predictors of engagement in protest is the appeal of the frame to the collective identity of an individual [221]. Splitting the hardship into multiple dimensions, as explained in the previous subsection, opens up a (new) way to implement a riot frame into a model. As each hardship dimension represents a different reason for which the agent can be aggrieved, the riot frame can be described along those same dimensions and grievances, and agents can measure the degree to which their own hardship corresponds with what they perceive the riot to be about.

The frame of the riot trigger is described in the model by  $F$ . The riot frame is the event that the agents perceive to be what the riot is about.  $F$  is expressed along the same non-negative dimensions as the hardship of agents.  $F$  describes the degree to which the riot concerns the different issues that are represented by each dimension. For example, the riot can be about a single issue (e.g. the social status of a single group), or be related to multiple issues (e.g. income and housing). For simplicity  $F$  remains fixed during my simulations, although it would also be interesting to investigate how frames would change over time, for example through interactions with responding police forces, changing the perception of the agents.

Similar to the hardship  $H$  of agents, I describe  $F$  using polar coordinates. In this thesis I only consider the special cases where the radius is  $F$  is 1 ( $\sum_i^D F_i^2 = 1$ ). This has the added benefit that when I only use one hardship dimension in the model, the hardship values are unaffected and the model reverts back to a comparable state with other models, because the overlap between the riot frame and the hardship is then determined by the hardship only.

## 3.4 Agent Age

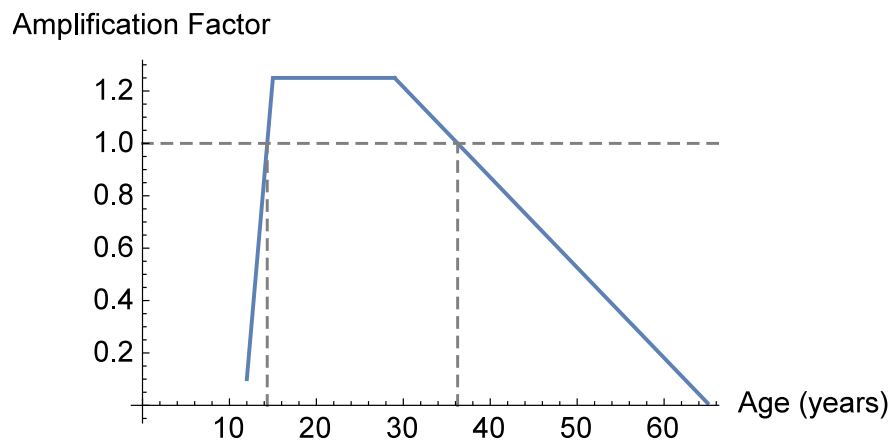
One component that has not been addressed yet in numerical models of civil violence is the effect of age. Different studies have highlighted the importance of age on the incidence of conflict, especially in riot situations [117, 196, 215]. Despite overwhelming evidence that certain age structures are highly predictive of conflict [45], this has not yet been incorporated into models. Particularly it has been shown that so-called youth bulges, where there is an abundance of males aged between 15 and 29, combined with poor socio-economic opportunities highly correlate with violence [45, 78, 175]. The importance of age is also reflected in the arrests record of the 2011 London riots (see Table 2.2) [127].

I therefore convolve the hardship level of each agent with an age-dependent factor that amplifies the hardship level of an agent between 15 and 29 years old and dampens hardship levels of agents outside that age band, reflecting the general age profile of arrestants in the London riots [127]. This is similar to the concept of risk aversion proposed by Epstein. In his model the agents are given individual risk aversion (or rather risk appetite) values that are multiplied by (local) arrest probabilities (see Section 3.11 for more details) to obtain an individual net perceived risk for each agent [55]. Individuals between the ages of 15 and 29, especially in deprived situations, typically have less to lose and more to gain from joining a riot, therefore increasing their propensity to join a riot [45]. The age convolution is therefore similar to the concept of risk aversion proposed by Epstein, but is based on demographic data rather than a (second) random (uniform) distribution.

The age-dependent factors are defined as:

$$f(A^i) = \begin{cases} \frac{23}{60} \cdot A^i - 4.5 & 12 \leq A^i < 15 \\ 1.25 & 15 \leq A^i < 29 \\ 2.25 - \frac{A^i}{29} & 29 \leq A^i, \end{cases} \quad (3.2)$$

where  $A^i$  is the age of the agent. For numerical reasons, agent hardship is capped at one. The amplification factors are also shown in Figure 3.1. The amplification factors are chosen such that agents between the age and 15 and 29 receive a small boost (25%) in hardship, reflecting their increased propensity to engage in violence [45, 127]. Furthermore for the remaining agents the amplification factors are obtained by drawing straight linear functions towards the boundary ages of 12 and 65, reflecting the arrest records of the London 2011 riots [127].



**Figure 3.1: Age amplification factor.** *The hardships of the agents are convolved with the age amplification factor to adjust their riot propensity. The hardship levels of agents between the age of 14 and 36 are boosted, while the hardship levels of agents with other ages are dampened.*

## 3.5 Riot Locations and Contact Network

Contact networks between individuals play an important role in spreading information about events like riots. Already during the riots in the USA in the 1960s, slightly less than half of the individuals that were arrested found out about the riot through interpersonal contact [176]. Through the adoption of online social media, the opportunities for individuals to share information and organise have increased. Particularly the ability to send messages to large groups of people simultaneously has greatly increased the speed by which information can travel through interpersonal networks. A particular focus of many studies into current events of civil unrest has therefore been on the role of online social media (e.g. [14, 21]).

Surprisingly, many of the current numerical models of riots do not include social networks between agents or effects of information sharing (e.g. [48, 55, 198]), with the exception of the work of Siegel [173, 174]. In my model agents have the ability to communicate with other agents and transfer knowledge about the riot along a pre-defined contact network. Additionally events of civil violence like the London riots and the Arab Spring that both occurred in 2011 are spread out over multiple locations where police clash with civilians. In my model I therefore describe multiple potential coupled riot locations, such that I can study the spread of violence from one location to another in Chapters 5 and 6.

The agents are divided equally over all the potential riot locations, and are limited to riot only at the specific location they are assigned. The reason that agents cannot engage in riots in other locations in the model is that information from the London riots showed that many individuals engaged in violence close to where they live [18], and that the likelihood of individuals travelling to another area is very small. The contact network for the agents is generated in two stages. First I describe separate local contact networks between the agents at every riot location. These local contact networks at the riot locations represent clustered communities. In the second stage I connect these clusters to couple the riot location and facilitate the travel of information between communities. The whole network can be viewed as a set of clusters that have a high internal density, and are more sparsely connected to each other. In this way the network emulates a set of cities or countries, where individuals are more likely to be acquainted to those who live in their own area than to those who live further away. The degree to which connections are preferred internally within the cluster versus externally to other clusters can be controlled through parameters.

The contact network between the agents for each potential riot location is described by a small-world network [173, 174, 211]. The standard procedure to generate this network the agents are placed on a ring lattice, where each agent then connects to its  $k$  nearest neighbours in the clockwise direction, such that the total number of edges per agent is then  $2k$ . Each edge is then rewired with a probability  $p$ , called the *rewire probability*, to another randomly chosen node in the network. Rewired edges cannot be self-loops or be duplicates of existing edges. The result is then a small-world network, where  $p$  describes the degree to which the network is a fully random network. I slightly adapt the above network generation algorithm in order to link the separate networks for each riot location to each other.

The rewire probability  $p$  in the standard small-world network generation algorithm describes the probability of each edge to be rewired to another randomly chosen node from its initial default position. Additionally to the rewire probability  $p$  I define two other probabilities:  $q_{\text{in}}$  and  $q_{\text{out}}$ . If an edge is rewired with probability  $p$ , it is then rewired to another node within the same network with probability  $q_{\text{in}}$ , or to any node that does not belong to that same network with probability  $q_{\text{out}}$ , such that  $q_{\text{in}} + q_{\text{out}} = 1$ . The result is one big network where the riot locations are represented as dense clusters generated by each individual small-world network.

The reason for using small-world networks to describe the contact network for these riot locations is that important online social networks like Facebook have a similar underlying structure [218]. Moreover, the underlying algorithm that generates these networks allows for explicit control over the key network characteristics, such as the network size, density, and structure. Because the network that I describe consists of multiple coupled riot locations, I need this explicit control to consistently create a network of coupled clusters that matches the configuration of the riot locations. Although clustering naturally occurs under some conditions in small world networks [211], these clusters can only be identified after the network has been generated. Using this approach in my model to describe each cluster as its own small-world network I can predetermine the important properties of the clusters (e.g. the location of the cluster in the network, size, density, and interconnectivity with other clusters), rather than having to identify them afterwards. This is important because in stochastic generation of networks, not every configuration that is generated will have the desired properties, and hence will have to be rejected until another repeated attempt with the same parameters yields a satisfactory result. With multiple rejections this process can be very time consuming and being able to control and predetermine the relevant



### 3.5 Riot Locations and Contact Network

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properties of a network a priori can thus save computing time. Moreover this method assures consistency when running the model multiple times, as I do not have to reject network configurations with undesired clustering characteristics. In Chapter 4 the riot locations are independent of each other, which allows me to take a different approach that generates contact networks that are more like those in the real world, based on data from a real world social network.

#### 3.5.1 Communication

In addition to defining the riot location of the agent the contact network also enables them to share information with each other, for example knowledge about the riot. Initially the agents, except those who start the riot, are unaware that there is a riot going on. The agents that do have knowledge of the riot can alert neighbouring agents in the network to the existence of the riot. The probability of an agent communicating to another random agent in its direct communication network (first-degree) is described by:

$$P(X = \text{communicate}) = \alpha \cdot e^{-\omega T_M}, \quad (3.3)$$

where  $\alpha$  is the average communication rate, and  $T_M$  is the number of iterations since the agent was last updated with information about the riot. Finally  $\omega$  is the memory capacitance of an agent, or conversely the rate at which the information degrades. Using this formulation the agents communicate less as the time they have last been updated about the riot progresses, considering the information outdated and no longer worth sharing. Also agents only communicate knowledge about the riot with others if the agent is in the same location as where the riot is taking place. Agents that are in the riot communicate with probability  $\alpha$  as their physical presence in the riot keeps them perpetually updated.

## 3.6 Joining & Leaving Riots

After the riot has started agents that know that there is a riot going on are able to join and support the riot each iteration of the model. This section describes the probabilities of agents to join and leave riots, depending on their current situation.

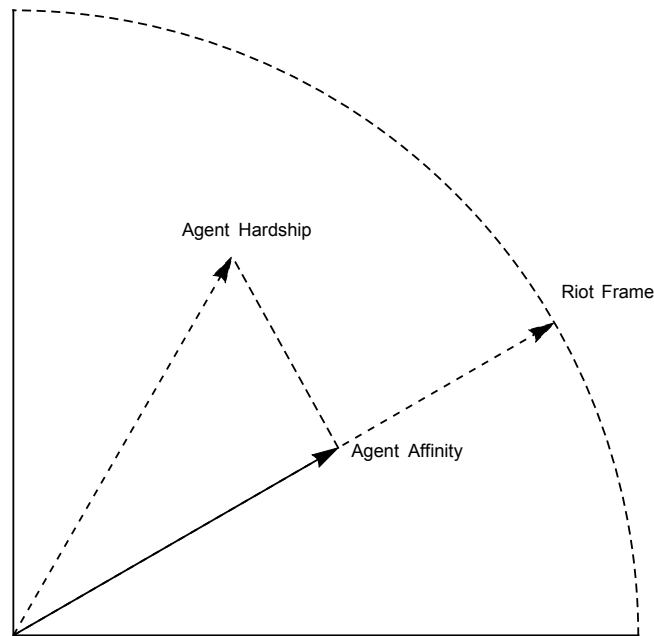
Following the example of Siegel [173, 174] I consider the probability that an agent will join a riot to consist of three components: 1) The internal motivation  $I$  of individual agents, 2) the external motivation  $E$  consisting of contributing environmental factors surrounding the agents, and 3) the repressive component  $R$  that deters agents from joining. In this section I define the mathematical equations that I use to calculate these separate components, and explain they are combined to obtain the final probability that an agent joins the riot. For the agents that are in the riot I calculate the probability that they will leave, which is partly driven by the external motivation and the repression.

### 3.6.1 Internal Motivation

The internal motivation  $I$  of an agent is the part of the motivation of an agent to join the riot that is related to the hardship of that agent. I define the internal motivation  $I$  as the affinity of an agent with the goal of the riot, computed as the dot product between the agent hardship levels  $H$  and the riot trigger  $F$ :

$$I = \sum_i^D H_i \cdot F_i. \quad (3.4)$$

The dot product describes the ‘overlap’ between two vectors. The outcome of the dot product is a scalar rather than another vector, and can also be interpreted as the radius of the smallest projection of two vectors onto each other. Because in our model  $F$  and  $H$  have radii between 0 and 1, the dot product between these vectors is also a number between 0 and 1. If  $H$  and  $F$  are perfectly aligned, the affinity or internal motivation  $I$  will be 1, and if there is an angle difference or the radius of  $H$  is less than 1, consequently the affinity will be lower. An example is shown in Figure 3.2.



**Figure 3.2: Overview of agent internal motivation  $I$ .** The dot product between the agent hardship  $H$  and the frame of the riot goal  $F$  describes the affinity of the agent with the riot. The riot frame  $F$  and agent hardship  $H$  are denoted by dashed arrows, the affinity of the agent or internal motivation  $I$  is denoted by the solid arrow.

#### 3.6.2 External Motivation

The external motivation  $E$  of an agent describes environmental influences. In this model the external motivation is defined by the support an agent has from other agents in its direct contact network. Studies have shown that the decision to join in rebellious collective action is often taken in groups [92, 119]. The effect of external propensity in the model is such that agents with low internal motivations can still be persuaded to join a riot if a large fraction of their social network is present in the riot. Similarly, agents with a high hardship level can be dissuaded by lack of support or reinforcement from their immediate social network.

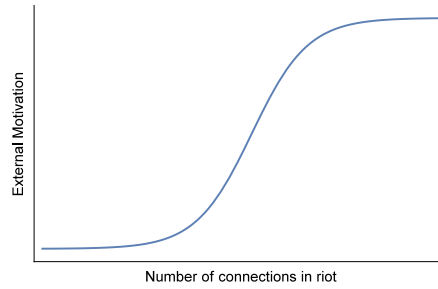
The external motivation  $E$  relates to the concepts of social embeddedness (see Section 1.6.4) and critical mass (Section 1.4). The location of the agent in the network becomes important through the environmental influence of the decisions of the direct contacts of the agent. If the agent is surrounded by other agents that all have a high internal motivation, that agent will be more likely to participate throughout the whole riot period; the social embeddedness of that agent is what exogenously drives the decision to participate in the riot. In the same way a dense cluster of motivated agents

can provide the initial critical mass necessary to start the riot.

The external motivation is described as

$$E = \frac{e^{\beta \cdot C_R - \gamma}}{1 + e^{\beta \cdot C_R - \gamma}}, \quad (3.5)$$

where  $C_R$  is the number of direct connections the agent has that are currently in the riot, and  $\beta$  and  $\gamma$  are control parameters based on the mean degree and variance in degrees of the network. I use a logistic function to model the at first increasingly, but later decreasing importance of group size. An example of the shape of such a function is shown in Figure 3.3. By using a logistic function, the external motivation increases slowly at first, but as the agent knows more other agents that are also participating, the propensity to join quickly increases. This effect eventually saturates, such that each further increase in the number of connected agents that participate has less effect than the previous one. Similar patterns of recruitment have also been detected in online protests [70].



**Figure 3.3: Example of a sigmoid function.** *In a sigmoid or logistic function the initial increase is slow, but increases exponentially. After the inflection point the decrease is initially rapid, and then slows down.*

### 3.6.3 Efficacy and Repression

The third component of the decision of an agent to join the riot is the repression  $R$ . In response to the riot the police raises the number of police officers, described further in Section 3.8. An increased number of police officers increases the risk of arrest and injury, which the agents take into account when considering to join the riot.

The repression  $R$  is defined by the fraction of number of rioters  $N_R$  relative to the sum of rioters and police officers  $N_P$  (Equation 3.6) and is the same for all agents. It is a crude measure of how safe it is for an agent to participate in the riot, and may be

### 3.6 Joining & Leaving Riots

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a true or perceived version of reality that is updated at every time step. I include a parameter  $\delta$ , *deterrence*, to describe the perceived threat of the police to the rioters:

$$R = \frac{N_R}{N_R + \delta \cdot N_P}. \quad (3.6)$$

The repression actually describes the *efficacy* of the riot that the agents take into account when deciding to join [92, 184, 221]. The efficacy is the reverse of the repression; when there are few police officers the value of  $R$  is high, which actually corresponds to little repression and high efficacy. Conversely when rioters are outnumbered by the police the value of  $R$  drops considerably, lowering the perception of efficacy of the riot because of the increased risk of injury and arrest.

#### 3.6.4 Joining Riots

The final probability of an agent joining the riot is described as a combination of the internal and external motivation and the police repression. The internal and external motivation are averaged into a single motivation upon which the repression acts. Additionally the interest of an agent in joining the riot declines as the information that the agent possesses about the riot becomes increasingly outdated like in Equation 3.3:

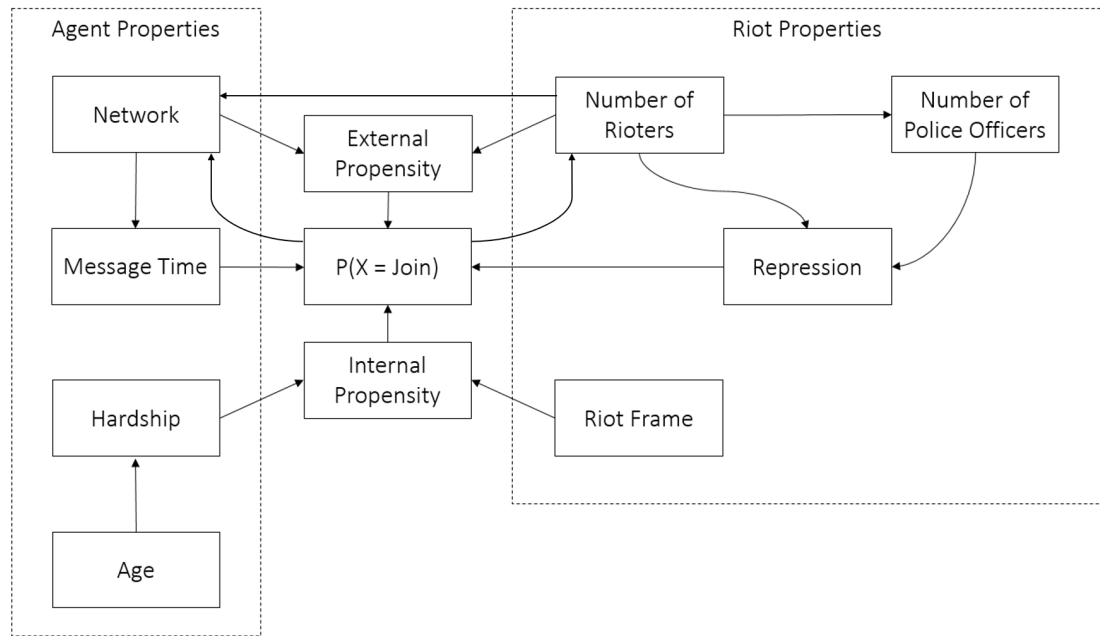
$$P(X = \text{join}) = R \cdot \frac{I + E}{2} \cdot e^{-\omega T_M}. \quad (3.7)$$

Figure 3.5 gives an overview of the variables involved in the decision of an agent to join the riot.

#### 3.6.5 Leaving Riots

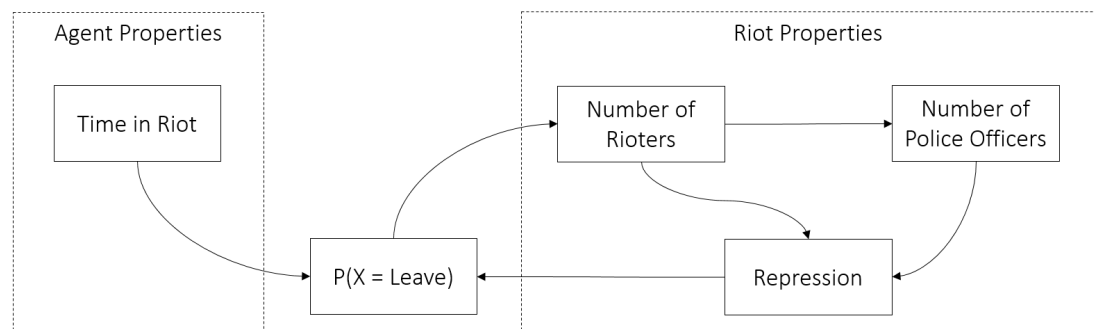
Agents that have joined the riot subsequently have the option to leave. The probability that an agent will leave the riot is defined as a combination of the repression or efficacy  $R$  and the time  $T_R^i$  an agent has spent in the riot since joining:

$$P(X = \text{leave}) = (1 - R)(1 - e^{-\varepsilon \cdot T_R}), \quad (3.8)$$



**Figure 3.4: Overview of relationships between agent and riot properties in agents joining riots.**

where  $\varepsilon$  is the *fatigue rate* related to an endurance clock that is associated with the onset of physical fatigue, so that the longer an agent is in the riot environment the more probable that the agent will leave. The decision to leave is then based on the fatigue of the agent and the risk of staying in the riot. Once an agent has left, it is unable to re-join the riot for a given (fixed) amount of time called the *cooldown* period.



**Figure 3.5: Overview of relationships between agent and riot properties in agents leaving riots.**

## 3.7 The Start of the Riots

The first riot in the model is manually started (forced) in a single riot location, by placing  $N_{R0}$  agents into the riot selected proportional to their affinity  $I$ . After the start of this first riot, agents in that same riot location can join and leave the riots every iteration, and the police in the model starts responding to the existence of the riot. As such, I assume that a riot always occurs in the model, and focus on the resulting dynamics rather than investigate which initial conditions lead to violent outbursts. However, under some conditions the start of the riot ‘fails’, for example through low agent motivation or overwhelming initial police presence and response, such that every agent that is at the start leaves (almost) immediately.

Some riots, such as the London 2011 riots, continue for more than a single day [161]. Additionally riots also spread to other locations. After the first riot in a single location is over in the model, there is opportunity for the riots to spread to other locations and restart at the same location. All agents who have been informed about the riot consider to start another riot the next day at the same start time of the initial riot, including agents at the other riot locations. Only those agents that have been alerted about the riot and are not on cooldown can consider to join the start of the new potential riot. Starting the riot at the same time everyday in the model results in a pre-defined periodicity, based on the diurnal pattern in the data from the London riots [122] and from other riots [120]. More (quantitative) research into the probability that certain conditions will lead to (the start of) riots would be helpful in creating a more dynamic solution, that does not rely on the forcing of the start of an event.

When the number of rioters  $N_R$  becomes zero, the repression or efficacy  $R$  also becomes zero, and consequently agents cannot join the riot any longer (Equation 3.7). This prevents agents joining a riot that is not in progress, and also prevents the start of a new riot. To restart the riot in the first location, or to start a new riot in other locations, the agents construct an *anticipated local number of rioters*  $N_R^L$ , that is individual to the agent. The next paragraph explains how agents calculate  $N_R^L$ .  $N_R^L$  describes the locally (to the agent) expected number of individuals that are at the start of the riot. Using  $N_R^L$  as a temporary substitute for  $N_R$  until the actual start of the riot, the agents can forecast the (perceived) repression  $R$ . The process for self-starting a riot by the agents is then as if they are joining an existing riot, rather than starting a new one.

At the time of a potential new riot all agents that know about the riots from the

previous day and are not on cooldown can decide to join the start of the riot with probability  $I$ . These agents together form the potential global riot start size  $N_R^G$ . The agents within  $N_R^G$  construct a locally perceived riot start size  $N_R^L$ , calculated as the fraction of their peers they have that are in  $N_G^R$  multiplied by  $N_R^G$ . The probability that an agent then participates in the start of the riot is the same as the probability of an agent joining the riot, but by substituting  $N_R$  for  $N_R^L$ .

If the a riot in a certain location fails to attract enough participants, or is very short in duration, the agents consider the riot to be finished and will not re-attempt to restart a new riot the next day. The exact values for these constraints are presented in Chapters 5 and 6. Additionally if from the start of a new riot the riot size decreases at all subsequent iterations the riot is also considered to be over.



## 3.8 Police Response

Some previous studies have considered the police response to riots as a fixed number of police officers with random movement [48, 55, 198]. In real riot situations the number of police officers increases rather than remains constant, and the police would concentrate on the areas where the riots take place rather than move around randomly. Such responses have not adequately been described as of yet in numerical models of riots [215]. To allow for a more dynamic police response involving different levels of repression I model the number of police officers  $N_P$  as a variable single number, rather than as a collective of individual police officers. After the agents decide to join and leave riots each iteration, the number of police officers is updated to according to the new riot situation.

Prior to the start of the riots the number of active police officers  $N_P$  is initialised as the minimum number of police officers  $P_{\min}$ . I also define a maximum number police officers  $P_{\max}$ , i.e. the total police capacity, to prevent unrealistically large police responses. As Figure 2.1 from the 2011 London riots shows, the peak number of police officers increased exponentially in the first four days of the riot. Following this general pattern,  $P_{\max}$  increases by 20% every 24 hours in the model. This raise in the maximum amount of total police officers represents the aid from surrounding areas such as during the 2011 London riots [121].

The police respond to the riots by increasing the number of police officers  $N_P$  at the relevant riot location. The number of police officers increases with a fixed rate of 10% if the police are outnumbered, or if the number of rioters increased in the last iteration, or has remained stable. If the number of rioters increased or has remained stable, more officers are necessary from a repressive point of view. Additionally the police are at a disadvantage as long as they are outnumbered. The proportional increase in police officers relative to their current number causes a snowball effect when attempting to contain a riot. For example, if the riot increases despite 50 extra police officers, the increase in police officers the next iteration is even higher.

The daily minimum number of police officers during the London riots increases in a straight line (see Figure 2.1). Therefore the minimum number of police officers  $P_{\min}$  increases by 10 police officers for each iteration of riot activity, such that there is an increased police presence even in the absence of riot activity. Moreover the higher minimum number of police officers also increases flexibility of the police response

to potential future unrests, due to the higher rate at which police can increase their numbers.

If the riot in the model stops ( $N_R = 0$ ), then the number of police officers  $N_P$  decreases by 10% every iteration down to the minimum number of police officers  $P_{\min}$ . If there is no riot activity for more than 24 consecutive hours in the model,  $P_{\min}$  decreases by 10% every iteration until the initial number of minimum police officers. The perceived threat is then over, and the increased police presence necessary to quickly react to new outbursts of violence is no longer necessary. The number of police officers therefore reverts back to the situation prior to the riots.

# 3.9 Chapter Variations

Each chapter uses a slight variation on the core model presented above to address the specific research question. This section summarises the differences between those variations and the core model. Each chapter contains a summarised version of the model, only describing the mechanics and equations.

## 3.9.1 Chapter 4

I demonstrate how the model can be applied to ‘predict’ or describe the London riots. Specifically I show how the model reproduces the key behaviour in three different boroughs during the riots. Additionally I use the model to investigate how gatherings preceding the riot influence riot behaviour, look at different police responses, and study the effect of information accuracy for the police response.

In order to study the effect of protests preceding the riots I prepend a module to the core model that describes a gathering between the agents, representing a peaceful protest or demonstration. During this phase the agents communicate their grievances to each other, influencing each other’s opinions.

Moreover the model in Chapter 4 uses a specific network configuration generated using a different algorithm than described in Section 3.5 in order to create a more realistic network structure. This approach is possible because the three riot locations are modelled independently of each other, rather than in a single integrated network as described in Section 3.5. This network is based on data from a real world social network [167].

To apply the model to the London riots some of the concepts in the core model are left out. The hardship of the agents is only described using a single dimension, making it more comparable to other models. Additionally I only describe one continuous riot, leaving out the possibility to regroup and restart the riots after the number of rioters drops to zero. Because of the inclusion of a protest prior to the riot, all agents also know about the riot from the moment it starts.

One of the goals of Chapter 4 is to demonstrate how a ‘general’ model can be applied to a specific event, in this case the 2011 London riots. The generality of the model refers to the motivation of the agents, which is based on concepts that theoretically can be associated with any riot, rather than a specific motivation that

only applies to a single event. To match the model behaviour with the data on the 2011 London riots, the model used in Chapter 4 uses a different police response than presented in this chapter. This alternative police response is based specifically on characteristics observed from the data described in Chapter 2, and consequently also targets that specific behaviour rather than a more general police response as described in this chapter.

### 3.9.2 Chapter 5

The largest difference between the model used in Chapter 4 and 5 is that whereas the model describes independent riot locations in Chapter 4, in Chapter 5 I investigate how and under which circumstances violence spreads from one location to another. Specifically I study the effects of the communication network, the collective identity of agents, and the frame of the riot trigger on coalition forming between communities that have different hardships or are aggrieved for different reasons. Because this study is not focused on any particular real-world location, the effect of age as described in Section 3.4 is left out.

### 3.9.3 Chapter 6

Chapter 6 uses the model as described in this chapter, with an additional process to structure information in the network. I use this to cluster agents together in age groups such that agents with a similar age are more likely to be in each other's direct contact network.

## 3.10 Model Metrics and Analysis

To analyse the model behaviour in Chapters 4, 5, and 6 I use multiple metrics to measure differences between alternative initial conditions. This section describes the metrics used in each chapter and discusses why in some cases I choose the median over the mean.

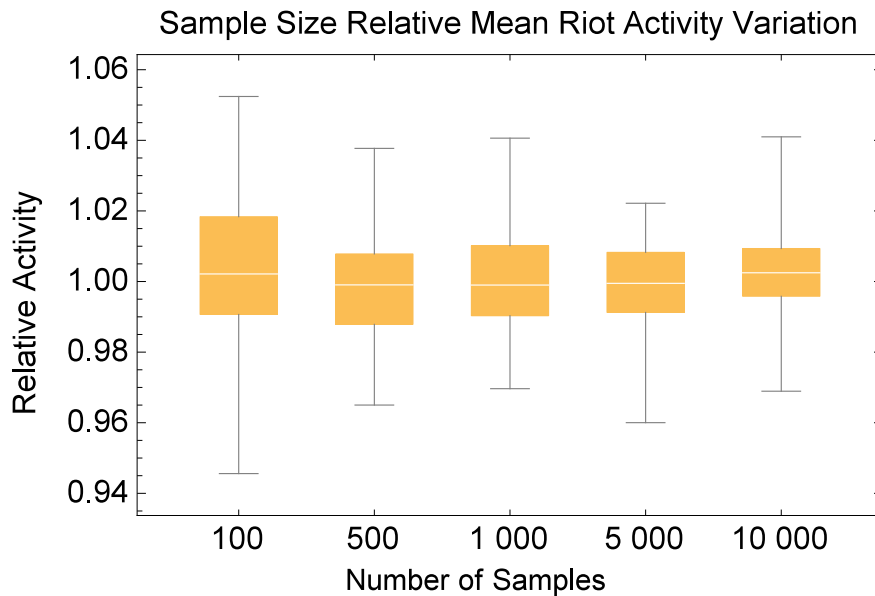
The first metric is the *total riot activity*, measured as the cumulative number of rioters during all iterations. Likewise the *total police activity* is measured as the sum of all the active police officers for all iterations in the model. I also obtain the *peak* number of rioters and police officers for each model run.

Another important metric next to the activity is the *riot duration*, calculated as the time between the riot start and end. Additionally I also calculate the number of *riot episodes* and the *live time*. The episodes are calculated as the number of continuous outbursts of violence. The live time is the amount of iterations the number of rioters was not zero. The riot duration, number of episodes, and live time are related and always indicate the same results throughout my experiments. Still these different metrics can be useful to discriminate between different types of riots. Some riots might have the same total duration, but with a different number of episodes or episode length, reflected by the total live time.

In the model used in Chapters 5 and 6 the agents initially do not know that there is a riot going on, except those who start the riot. The agents that are in the riot communicate their knowledge about the riot to other agents through the contact network, who can repeat this and disseminate the information further. I track the number of agents who know about the riot in the model during each iteration, and keep track at which times half, and all of the population knows about the riot (*full* and *half time*). Because for some parameter settings the riots stop relatively quickly, the information does not always spread far enough to reach all agents, so I cannot always obtain values for these metrics.

Because the model is stochastic I run the model multiple times (1,000 to 10,000 samples) at each parameter setting to obtain the full range of behaviour. By using a simple model I explore the statistical features of the ensemble. For each of the model runs I calculate the values of the above metrics, and from that ensemble I determine the mean, median, and variance associated with each metric. Figure 3.6 shows the

range of the mean riot activity in the model obtained after a different number of samples. 1,000 samples is generally sufficient to generate a similar result as increasing the resolution 10,000 sample runs.



**Figure 3.6: Spread of relative mean riot activity at various sample sizes.** I run the model multiple times (samples) to create an ensemble from which I obtain the mean, median, and variance of a metric. The riot activity is computed as the sum of the number of rioters over all iterations in the model (10 days). For a superset of 100 samples I show the range of values obtained for the mean riot activity at different sample sizes. The mean riot activity is expressed relative to the mean of all samples together. The black lines denote the minimum and maximum values, the inner yellow box the first and third quartile, and the white line the median.

In Chapter 4 the model describes one continuous riot, whereas Chapters 5 and 6 describe a riot that can be restarted the next day (see 3.7). In those chapters I calculate a *riot probability* for each day as the fraction of all model runs that have riot activity on that day.

Chapters 5 and 6 describe multiple coupled riot locations, whereas in Chapter 4 the riot locations are considered to be independent (see Section 3.9 for more details). Therefore in Chapters 5 and 6 I calculate the metrics for each riot location, as well as for all riot locations together.

Lastly for each chapter I also present a base model run, that I use as a reference point for comparison with other parameter settings. In this base run I show the model behaviour for each iteration, such that the diurnal cycles of the riots, the peak times,

### 3.10 Model Metrics and Analysis

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and other dynamics are clearly presented. At each iteration for each sample I calculate the mean riot level for that iteration, as well as the median, minimum, maximum and first and third quartiles to be able to analyse the spread of behaviour in the model. When presenting the riot behaviour for each iteration I choose to show the median over the mean, because the mean gives a skewed impression of riot activity when many model runs no longer have any riot activity. The mean activity remains positive as long as all but one model run has stopped (i.e. outlier), which can give a wrong impression of the riot activity.

### 3.11 Arrests

Unlike previous models of riots, the model that I use does not include a mechanism for arresting agents by the police (e.g. [48, 55, 198]). The removal of agents through arrests made by the police was not left out because such processes have a negligible impact, but for other reasons discussed in this section.

The first reason is that I could not find an equation that satisfactorily matched with the data of the 2011 London riots. The dataset on the London riots (described in Chapter 2) contains the number of hourly arrests made in each borough. My first attempt at including arrest was to use the equations described by other studies. Epstein proposes the following formulation in his model:

$$P(X = \text{arrest}) = 1 - \text{Exp}\left[-k\left(\frac{C}{A}\right)_V\right]. \quad (3.9)$$

$(C/A)_V$  describes the ratio of police personnel ( $C$ ) and active rioters ( $A$ ) within the range of vision  $V$  (e.g. a grid cell). Parameter  $k$  is set such that the probability of an agent getting arrested is 0.9 when there is 1 active rioter and 1 police officer (i.e.  $k \approx 2.3$ ) [55]. Similar definitions for the probability of arrest based on Epstein's formulation have also been used in other agent-based models of civil violence [48, 198].

Epstein's proposition makes sense when only considering 1 rioter and 1 police officer, it is not supported by the data for the London riots. Epstein's formulation of arrest can be used to infer the number of active rioters of crowd size during the 2011 London riots by using the MPS data on the number of arrests and active police officers during that period:

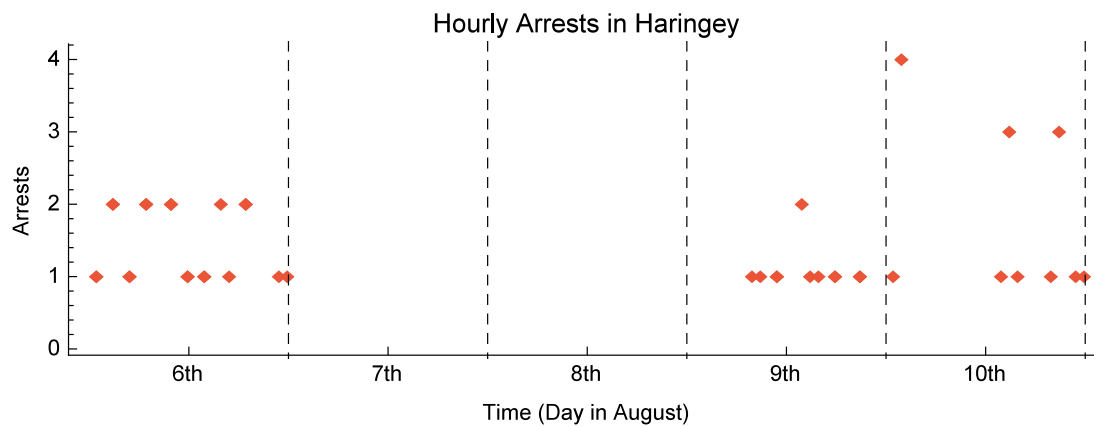
$$\frac{\text{Arrests}}{\text{Crowd Size}} = 1 - \text{Exp}\left[-k \cdot \frac{\text{Police}}{\text{Crowd size}}\right].$$

The results of the inferred crowd size does not match up with the data on the number of calls during the London riots, both for the whole of London as well as for the individual boroughs. One potential problem is that the formulation of arrest as proposed by Epstein revolves around very local conditions [55]. The probability of arrest is determined by the ratio of active police officers and rioters within a vision  $V$ , spanning a couple of grid cells. The data on the London riots is at the level of individual boroughs, a significantly lower spatial resolution. However the number of



### 3.11 Arrests

hourly arrests in the boroughs is very low; for example in Haringey where the riots started the police did not arrest any people during many hours, and the maximum number of people apprehended during a single hour is four (see Figure 3.7). At higher spatial resolutions the number of arrests become even lower, despite a significant number of rioters and active police officers in the region [121]. It could be that the formulation proposed by Epstein does not work for the London riots specifically, because the main focus of the MPS during the first days was to contain the riots rather than arrest rioters [121].



**Figure 3.7: Hourly arrests in Haringey during the London 2011 riots.** *Based on the MPS dataset [122].*

The second reason for not including arrests in my model is that the effects of apprehending individuals on civil disobedience have already been thoroughly investigated by Siegel [173, 174]. In his work arrests do not only have an effect on the total riot population, but also on the flows of information because these agents are no longer able to communicate with other agents and spread information. By using multiple network topologies Siegel finds the conditions under which arrests are an effective approach and when the impact is negligible, and the influence of arrests on participation in collective action.

Another consideration is that the cooldown mechanism included in the model is somewhat similar arrests, as it does not allow the agent to participate in riot activity for certain of time. The two key differences between agent cooldown and arrests is that 1) every agent is subject to a cooldown after participating, whereas with arrests it is possible that only a subset of those rioting are affected, and 2) the cooldown time of the agents is typically shorter than most jail terms prescribed in previous models [55].

## 3.12 Gillespie Algorithm

Two important aspects in agent-based modelling and other forms of numerical modelling featuring coupled systems, are *synchronicity* and *time resolution*. Synchronicity refers to how states in the model are updated. *Synchronous* models update all states in the model at the same time, such that a state change in one particular component does not influence another component during the update process. Conversely *asynchronous* models allow the individual components of a model to update independently of each other [66].

Considering how the model is updated is important, as asynchronous updating sometimes reveals behaviour that cannot be obtained by only considering synchronous updating. An example is the difference between the models of collective action using rational choice theory where the group behaviour is extrapolated from one individual, and the models proposed by Oliver and Marwell in their theory of critical mass [116, 139, 140]. In the early models of collective action the group decision is obtained by studying the behaviour of a single individual, as if they all decide at the same time (synchronous). Oliver and Marwell introduce *interdependence* between the decisions of individuals, such that earlier contributions towards a public good impact the decisions of others [139]. In their model the decisions of the actors are fully sequential, such that only one actor makes a decision at a time (asynchronous). Because of the impact that actors have on each other when updating independently, Oliver and Marwell were able to demonstrate the concept of critical mass that was previously unobtainable when decisions were considered to be taken synchronously.

The time resolution refers to the size of the time step in the model. In numerical simulations the time step is an important factor in determining the accuracy of the behaviour of the model, and can also impact the stability and dynamics. Very small time steps give greater accuracy but will result in more computing time. Too coarse time steps can result in artificial or wrong behaviour, such that systems that for example converge onto an equilibrium, can show signs of dampened, stable, or even forced oscillations around the equilibrium. Such oscillations are often used as an example in system dynamics, where systems that are known to converge towards a steady-state perpetually oscillate around equilibria due to their numerical simulation methods [186, 192].

The model presented in this chapter features synchronous updating every

### 3.12 Gillespie Algorithm

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iteration, and the timestep represents 30 minutes. To ensure that the model does not suffer from the same problems as described above, I use the Gillespie algorithm to verify that the time resolution and the synchronous updating of the agents and the police does not result in artificial behaviour.

The Gillespie algorithm is a simple and straightforward way to numerically simulate stochastic systems that can be divided into individual (coupled) processes [67, 68]. It automatically updates the model at the highest necessary time resolution. Additionally all the states in the model are updated fully sequentially.

The algorithm works as follows; consider two events  $A$  and  $B$  (e.g. agent  $X$  and  $Y$  joining the riot) that occur with probabilities (or rates)  $P_A$  and  $P_B$  at the current time  $T$  in the model. The total probability of an event happening  $P_\Sigma$  in the current timestep is obtained by adding all the individual probabilities:

$$P_\Sigma = P_A + P_B. \quad (3.10)$$

The average time to an event  $\bar{T}_{\text{event}}$  is then calculated as:

$$\bar{T}_{\text{event}} = \frac{1}{P_\Sigma}. \quad (3.11)$$

Then by using an exponential distribution, describing the time between different events, the time  $\tau$  to the next event can be sampled:

$$\tau = -\text{Ln}(U(0, 1)) * \bar{T}_{\text{event}}, \quad (3.12)$$

and the old time  $T$  can be updated to the new time:

$$T_{\text{new}} = T_{\text{old}} + \tau. \quad (3.13)$$

To update the current state of the model to the next timestep  $T_{\text{new}}$  the algorithm finds which of the two events  $A$  and  $B$  occurred, by using the fractional probabilities  $\frac{P_A}{P_\Sigma}$  and  $\frac{P_B}{P_\Sigma}$ . Then the states can be updated (e.g. agent  $X$  joins the riot), such that  $P_A$  and  $P_B$  change and a new  $P_\Sigma$  can be obtained, and the algorithm can be restarted.

The Gillespie algorithm considers each possible state change in the model as a separate event, and stochastically generates the time to the next event. In general the algorithm therefore always runs the model at the highest necessary time resolution; if there is a high probability of events the timesteps will be very small, and if there are very few events the model will take large leaps with every timestep. There is also a disadvantage to using this approach, as the Gillespie algorithm can be inefficient and computationally expensive. As each event is treated separately, it can take many iterations to go through time period where there are high probabilities of many events occurring at the same time.

By using the probabilities described in equations 3.7 and 3.8, I have verified that a Gillespie version of the version of the model presented in Chapter 4 produces similar behaviour as the default method (see Appendix 8.3), where the time steps represent 30 minutes, and during each time step or agents and the number of police officers are updated at the same time. Thus when using synchronous updating and a fixed timestep in the model, which is computationally less expensive, no artificial behaviour is introduced in the model behaviour.

## 3.13 Riots and Differential Equations

Besides agent-based models I have also made attempts to model riots using other methods. Initially I used game theory, and later switched to differential equations. The advantage of using (ordinary) differential equations (ODEs) is that in some cases they can be analytically solved, such that numerical simulation is not necessary to obtain results. Moreover due to application of differential equations to many (mechanical) problems, and more than three centuries of use and development of such methods [136], the general dynamics of differential equations are well known and their use has become standardised in (applied) mathematics and physics.

Obtaining results from differential equations is easiest if they can be solved analytically. However when more elaborate concepts are included the complexity of these equations quickly increases, and it may no longer be possible to find analytical solutions. When implementing space for example, the ODEs become partial differential equations (PDEs), of which some still can be solved analytically [96]. Another important concept used in our model is memory, which would result in either delayed differential equations or integro-differential equations. Like PDEs, some of these can be solved analytically [96]. The model that is used in this work makes use of probabilities and is therefore stochastic instead of deterministic. Including stochasticity in differential equations makes it nearly impossible to solve them explicitly, except under very strict circumstances [138].

Using differential equations, I formulated a set of equations that could capture the general phenomena associated with riot behaviour, such as sudden outbursts of violence, a diurnal cycle, and fleeing from police. I found that implementing a police response to the riots was more problematic. The approach that I took to describe a police response was too algorithmic; 1) increasing riot activity was met with more police; 2) the number of police officers remained constant with declining riots; and 3) police activity only declined once riot activity had ceased for a certain amount of time. Additionally after riots are over, a continuous heightened presence must be maintained in case the riots are quickly followed by another episode. This algorithmic like response resulted in fragmented behaviour, where the behaviour of the police would instantaneously shift from one approach to another. Additionally restarting the riot after a period of rest required an artificial shock or perturbation to the system, which combined with the police response made it impossible for me to find analytical solutions.

Due to these problems I opted to use an agent-based model rather than differential equations. Moreover an ABM allowed me to 1) easily implement heterogeneities in the riot population, and 2) directly use the theories from social psychology (e.g. [92, 184, 221]) and implement them on the individual level in the agents. It is possible to capture the same behaviour of an agent-based model using differential equations: Zou demonstrates how Epstein's model of civil violence [55] can be described using PDEs [222], and is a good example of the mathematical complexity involved in capturing the dynamics of a simple ABM using differential equations. The differential equations that I used to create a riot model behaved similarly to the ABM described by Torrens [198]. One of my early prototype versions of a riot model using differential equations is described in Appendix 8.4, where I also show the main behaviour along with the similarities to the results of the agent-based Torrens model.

Despite my problems with formulating a mathematical model of riots using differential equations, others have shown that it is possible to achieve (e.g. [24, 25, 103, 104]). However the findings from these studies are hard to relate back to the real world. The work of Berestycki for example mainly focuses on overcoming theoretical and conceptual mathematical problems (e.g. 'the cauchy problem') encountered in using differential equations to model riots [24, 25], and as such has little results that actually relate to riots.



# CHAPTER 4

## Applying a General Riot Model to the London 2011 Riots: the Influence of Protests on Riots

### ABSTRACT

Improved understanding of the mechanisms underpinning riot dynamics can help to identify and mitigate risks and costs associated with riots. I describe a new generalizable and mechanistic agent-based model that predicts macroscopic properties of riot dynamics. I evaluate the model performance using data collected by the London Metropolitan Police during the London riots, 6-10th August 2011. The model reproduces observed changes in police officers on duty (Spearman's correlation coefficient  $\rho = 0.7-0.8$ ) and the number of incoming emergency calls (a proxy for the number of rioters,  $\rho = 0.3-0.6$ ) in the Haringey, Enfield, and Croydon boroughs of London. Sensitivity analyses of the interplay between pre-riot protests, riots, and the associated police responses show that a higher number of pre-riot gatherings generally increases the probability of a riot compared to one large-scale pre-riot gathering. I also show that a large, initial police (over) response reduces the probability and duration of a riot, and therefore places less stress on police resources over the duration of the riot. The rioter-police dynamic relies on the available intelligence to the police, such as knowledge about the riot size, and I find that incomplete knowledge amplifies the dynamical responses.

**Author Contributions:** This chapter is based on a paper that has previously been submitted. Jelte Mense, Paul Palmer, and Matthew Smith wrote the paper. Jelte Mense implemented the model, and conducted the experiments and computational analysis. The paper has been edited into this chapter by Jelte Mense.



# 4.1 Introduction

Western Europe experienced several large riots over the past decade, e.g. the Paris riots in 2005 [101, 171], the London riots in 2011 [161] and the Stockholm riots in 2013 [170]. During the London riots the police were surprised by the speed and intensity with which the violence spread [161]. Previous work has suggested that the widespread use of social media (Twitter and BlackBerry Messenger, in particular) to rapidly disseminate information may have exacerbated the situation [14]. The potential contribution of social media to the formation and progression of riots raises questions whether such events are now more likely to emerge, and further increases the urgency to improve understanding on which, and how, underlying causes and environmental conditions such as social networks lead to the rise and escalation of civil violence. I develop a general and simple (small number of tunable parameters) mathematical model to describe the onset (succeeding the underlying trigger) and evolution of a riot. The model allows me to explore quantitative and qualitative aspects of the dynamics of a riot to improve the systemic understanding of the underlying causal mechanisms.

There is a substantial body of literature about riots from various disciplines within social theory (e.g. [23, 92, 108, 120, 144, 151, 165, 184]). Mathematical models can be used to test and modify hypotheses originating from this literature, and to uncover and explore dynamical sensitivities that are difficult to study in real life. The use of mathematical models that incorporate and develop social theory associated with riot behaviour is not new. Some of the earliest models used behavioural thresholds to demonstrate how collective behaviour might lead to outcomes that do not seem intuitively consistent with the underlying preferences of an individual within the context of riots, such as phenomena that occur only after a threshold number of participants has been reached [72]. Recent work has relied on statistical models and analyses to infer relationships from data. For example, determining spatial movement patterns of individuals [16, 17], target choices [18], recruitment to riots using online networks [70], and the links between the frequency of civil unrest and variables that characterise changes in climate [27, 37, 38, 81, 82, 141, 157, 168]. Another approach to understand riots are agent-based models, in which agents (representing an individual or some collection of people) are given (preferably few) rules on how to interact with their environment and other agents (e.g., [48, 55, 198]). The crowd behaviour of riots is then obtained through the social interactions of these agents. One attractive property of this approach is the emergence of collective

behaviour that is derived from the ensemble of individual behaviours [77]. In order to leverage theory about the motivations of an individual to join a riot, I have adopted an agent-based modelling approach.

Two recent studies exemplify the spectrum of approaches that have been taken to describe a riot environment using agent-based models. One approach is to describe the decision of agents to join a riot purely based on general concepts such as hardship and risk aversion [55]. These concepts can be adapted for different kinds of riots but there is little further scope for any specificity to describe a particular riot. In contrast, another approach is to build a model on the specific behaviour of a particular riot. For example, incorporating the attractiveness of retail sites associated with looting that accompanied the 2011 London riots [48]. This approach is underpinned by a specific motivation and is consequently less applicable to other riots where rioters might have other motivations.

Here, I develop a model formulation that employs both generality and specificity: a model that uses general concepts to motivate agents to join the riots and also can be used readily to describe specific riots. In the broadest sense, my approach is focused on the motivation of the individual rather than the behaviour of the crowd, and describes different stages through which individuals are recruited for protests and riots [92, 184]. I have attempted to minimize the number of parameters that are used to describe the dynamics of a particular riot. The underlying philosophy of this approach is so I can 1) explore model parameter space to quantify the sensitivity of my results to changes in assumed values for exogenous and endogenous variables, and 2) explore different riot scenarios and police responses so I can understand the conditions that lead to the escalation of violence.

To obtain the behaviour of specific riots but base the motivation of the agents to join the riot on general interactions I introduce several new concepts, e.g. the consideration of the age distribution of the population and the influence of protests preceding the riots. Not all protests develop into riots, but at least 50% of riots are directly preceded by protests [120]. Notable examples of riots in Europe in the last decade which were also preceded by protests were the riots in Paris 2005 [171], London 2011 [121], Stockholm 2013 [170], Istanbul 2014 [203], and the Hague in the Netherlands 2015 [133, 207]. However, these riots did not in all cases directly develop from the preceding protests; in the Stockholm 2013 riots, there was a two-week period between a protest march organised by a local political youth group and the start of the riots [170].

Events of protests, riots, rebellions, and revolutions have all been studied by different academic disciplines driven by different methods. Social psychologists have had a specific focus on protests (e.g. [184]), collective action theory has been applied to both riots and rebellions (e.g. [118, 130]), and others have used the same numerical model to describe both riots and revolutions (e.g. [55, 129]), generalising them to the same activity. However, in some cases multiple and also different types of events can follow each other, such as in the examples mentioned in the previous paragraph, where protests are followed by riots. Another notable example is the Maidan revolution in Ukraine in 2014, where initial protests developed into riots, and eventually led to a revolution [99, 185]. As these types of events transition into each other, preceding events have the potential to influence and shape the conditions that lead to subsequent escalation into a different type of civil unrest. In the context of (the London) riots, this leads to the questions of how the outcomes and dynamics of riots are influenced by preceding protests, and to which degree riots are dependent on those events. Previously however, events of protests, riots, and revolutions have largely been studied in isolation or as one single event, rather than a set of different multiple events that cascade into each other.

The reason to include protests in the model is to investigate how collective actions preceding riots potentially influence riot dynamics and can help explain the subsequent evolution of an event. Protests and riots are associated with different behaviours; whereas protests are ideologically driven and can be peaceful, riots mostly lack such a common conviction and feature the use of violence (see Section 1.2). There are different mechanisms by which a protest can potentially influence a subsequent riot. One important factor in the motivation for an individual to join in a protest is the association with a collective identity [92, 184, 221]. Such a collective identity however, can be formed as much during as prior to events of protests and collective action [155]. As protests sometimes directly develop into riots, such as in the start of the 2011 London riots in Haringey [121], there can be an overlap in the motivation to join the protest and the riot. The influence of the protest on the collective identity of participants can therefore also strengthen the motivation to join the subsequent riot, and thus help create the initial conditions necessary for the escalation of violence. Moreover, protests can establish a bias in the perception of participants and induce a sense of (false) confidence, as they are temporarily surrounded by others who have the same or similar grievances, potentially raising the efficacy of the present group. Lastly, when a protest directly evolves into a riot, individual protesters can act as a potential pool for rioters. A riot preceded by a small

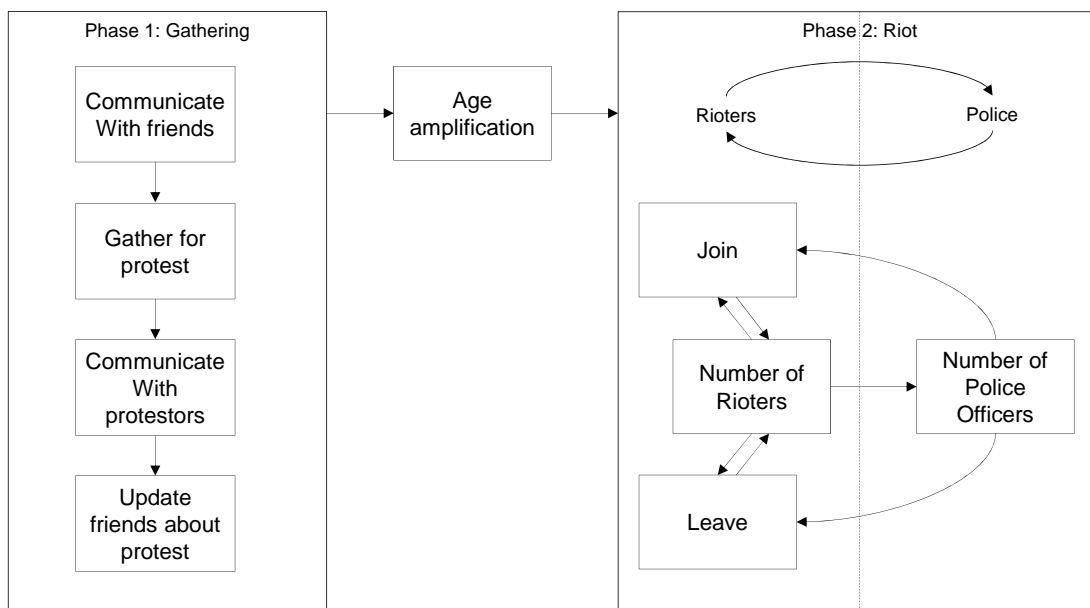
protest will consequently be easier to contain by the police than if it is preceded by a large protest, assuming that the propensity for individuals to join a riot is equal in both situations. Including a description of a pre-riot gathering in a model of riots can therefore potentially help explain why some riot behaviours and outcomes are different than others.

I evaluate the model using data about the 2011 London riots provided by the London Metropolitan Police Service (MPS). I apply the model to three different boroughs in London, which I chose because they represent a variety of behaviour within the riots: Haringey, Enfield, and Croydon. The riots started in Haringey on August 6th, in Enfield on August 7th, and in Croydon on August 8th. In this study I consider the dynamics of the riots in the three London boroughs to be largely independent, supported by previous studies on the London 2011 riots that demonstrated a strong exponential decaying relationship between the distance that offenders travelled from home to the place where they were arrested [18]. The event leading up to the 2011 London riots was the fatal shooting of a resident of the London borough of Haringey by the MPS on suspicion of carrying a firearm [121]. The shooting occurred on August 4th in Haringey, followed by an initially peaceful protest march on August 6th in the same area. The protest march ended at the local police station, where eventually protesters and police clashed. This escalated into the spread of violence across Haringey. In the days that followed, the riots evolved from violence against police officers to opportunistic looting and spread to multiple boroughs in London, and were related to outbreak of civil unrest in other large cities within the United Kingdom. The number of police officers trying to restore order steadily rose over several days with most of the riot activity concluded by August 11th.

The simplicity and modular framework of my model allows me to explore the importance of individual model sub-components to the riot dynamics. Here, I focus on three aspects of the riot dynamics. First, how does the size and frequency of pre-riot protest influence the probability of a riot? Second, to what extent can police tactics minimise that probability? Third, how does the accuracy of knowledge affect the probability of riot? Both in terms of rioter behaviour given their collective sense of real or perceived injustice and their estimated risks from participating in riots, and of the police response based on their estimated risk associated with the potential riot size and damages from the riot. I answer these questions by varying the relevant parameters and initial conditions in the model, and compare the resulting riot activity and duration with the 'reference' model run that reproduces the main dynamics of the riots in Haringey in London in 2011.

## 4.2 Riot Model Description

To answer the questions posed above I develop a simple and generalizable mechanistic agent-based model. In agent-based modelling so-called agents are entities who act by predefined behavioural rules. The model behaviour is obtained as a result of interactions between multiple agents and their environment. In my model agents represent potential individual rioters. The model is split into two chronological phases: 1) a pre-riot gathering (e.g. protests, demonstrations) and 2) the riot and the associated police response (Figure 4.1).



**Figure 4.1: Model overview describing the two phases of the riot model.**

At the start of the model each agent  $i$  is assigned an age  $A^i$ , based on local or regional demographic data, and some prior belief about an inequality that is parametrised by a hardship level  $H^i$ , describing the agents' discontent. The hardship is distributed according to a random uniform distribution [48, 55, 198]. The agents also have a contact network that connects them to other agents, based on a real world social network described in greater detail below [94, 167].

### 4.2.1 Pre-riot Gathering Phase

The pre-riot gathering phase in the model resembles a protest or a demonstration, where individuals come together to show their discontent about an issue. The aim of

this activity is to establish a communication mechanism in which similarly minded agents reinforce each others opinion, and agents with opposite viewpoints balance each other out. The final hardship of an agent then becomes dependent on its position in the network, as the hardship levels of the other agents one is connected to determines whether its motivation is dampened or reinforced. For example when an agent with high hardship is connected to similarly minded agents, the final result will be an agent that is further inspired to take action. Additionally agents with more extreme opinions will be less susceptible to the opinions of other agents, compared to agents that have more moderate hardship levels. The communication of hardship between two agents  $i$  and  $j$  with hardship levels  $H^i$  and  $H^j$  at time  $t$  is defined by

$$H_{t+1}^i = H_t^i + \alpha \cdot (1 - 2 \cdot |H_t^i - 1/2|)(H_t^j - 1/2), \quad (4.1)$$

where the ability of an agent to change the opinion of another agent is parametrised by  $\alpha$ . The value of  $\alpha$  is the same for all agents.

The gathering phase comprises of three rounds of communication. First, all agents communicate and update their hardship via a pre-defined social network. Second,  $N_G$  agents are randomly sampled, weighted by their hardship, to participate in a gathering (e.g., a peaceful protest march). The previously defined communication network is then temporarily replaced by a local network where all  $N_G$  agents are connected to each other (the complete digraph). The second round of communication then occurs on this new temporary graph. The participating  $N_G$  agents are returned to the general agent population where they update their hardship levels to other agents using the original social network.

In the final step before the model starts a riot, the hardship level of each agent is convolved with an age-dependent factor that amplifies the hardship level of an agent between 15 and 29 years old and dampens hardship levels of agents outside that age band. This is similar to the idea of risk aversion used by previous studies of civil violence [55], but is based on demographic data rather than a random distribution. Past work and data has highlighted the abundance of individuals between the ages of 15 and 29 in a society as a potential indicator of civil conflict [45], and is also reflected in arrest records of the London 2011 riots [18, 164]. Based on this work, I define the

## 4.2 Riot Model Description

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age-dependent factor as:

$$f(A^i) = \begin{cases} \frac{23}{60} \cdot A^i - 4.5 & 12 \leq A^i < 15 \\ 1.25 & 15 \leq A^i < 29 \\ 2.25 - \frac{A^i}{29} & 29 \leq A^i, \end{cases} \quad (4.2)$$

where  $A^i$  is the age of the agent. For numerical reasons, agent hardship is capped at one, such that the hardship level of agents cannot be amplified beyond this value.

### 4.2.2 Riot Phase

After the gathering phase I randomly sample  $N_{R0}$  agents from the general population, weighted by their hardship levels, to enter a riot. After the riot has started agents are allowed join or leave the riot at each successive time step  $t$ .

The probability of an agent joining a riot is defined by the: 1) internal propensity, the motivation to join that comes from within the agent, 2) external propensity, describing external influences, and 3) repression or efficacy level, which is the same for all agents. The internal propensity  $I$  of an agent is the hardship  $H^i$  of agent with index  $i$ . The external propensity  $E$  includes the influences from outside the agent, such as the number of connections  $C_R^i$  it has to other agents who are already in the riot.  $I$  and  $E$  are combined into a total motivation  $M$ , such that agents with low hardship levels can still be persuaded to join a riot if a large fraction of their social network is present in the riot. Similarly, agents with a high hardship level can be dissuaded by lack of support or reinforcement from their immediate social network.

First, I calculate the external motivation  $E^i$  of agent  $i$  to join the riot based on its connection with rioting agents:

$$E^i = \frac{e^{\beta \cdot C_R^i - \gamma}}{1 + e^{\beta \cdot C_R^i - \gamma}}, \quad (4.3)$$

where  $\beta$  and  $\gamma$  are control parameters based on the mean degree and variance in degrees of the network. Second,  $E^i$  is combined with  $I$  ( $H^i$ ) to obtain the total motivation  $M$ :

$$M = \frac{1}{2}(H^i + E^i). \quad (4.4)$$

The repression or efficacy  $R$  is defined by the fraction of number of rioters  $N_R$  relative

to the sum of rioters and police officers  $N_P$  (Equation 4.5) and is the same for all agents. It is a crude measure of how safe it is for an agent to participate in the riot, and may be a true or perceived version of reality that is updated at every time step. I include a parameter  $\delta$ , deterrence, to describe the perceived threat of the police to the rioters.

$$R = \frac{N_R}{N_R + \delta \cdot N_P}. \quad (4.5)$$

Combining  $M$  and  $R$  gives the probability that an agent will join the riot:

$$P(X = \text{join}) = R \cdot M. \quad (4.6)$$

Second, I calculate the probability of an agent leaving the riot as a combination of  $R$  and the time  $T_R^i$  an agent has spent in the riot since joining:

$$P(X = \text{leave}) = (1 - E)(1 - e^{-\varepsilon \cdot T_R^i}), \quad (4.7)$$

where  $\varepsilon$  is an endurance clock that is associated with the onset of physical fatigue so that the longer an agent is in the riot environment the more probable that the agent will leave. The decision to leave is then based on the fatigue of the agent and the risk of staying in the riot. Once an agent has left, it is unable to re-join the riot for a given amount of time called the cooldown period.

### 4.2.3 Police Response

I describe the police response as the total number of police officers on duty. The MPS data collected during August 2011 [122] shows that the number of police officers on duty during the London riots had a diurnal cycle with the minimum occurring each day around 0600. Consequently, I describe the number of police officers  $N_P[t]$  as a periodic function, with a constant offset to match the daily cycle in the MPS data. The amplitude  $A$  and the baseline  $B$  of the periodic function are described as a combination of the initial baseline  $B_0$  and amplitude  $A_0$  before the riots started and the extra number of police officers as a result of the riot ( $A_R[t]$  and  $B_R[t]$ ):

$$N_P[t] = (B_0 + B_R[t]) + (A_0 + A_R[t]) \cdot |\sin(\frac{\pi \cdot t}{48} - 0.9)|. \quad (4.8)$$



## 4.2 Riot Model Description

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The values of  $A_R[t]$  and  $B_R[t]$  (Equations 4.9 & 4.10) are calculated as a function of the past rioters activity  $R_\Sigma$  (Equation 4.11):

$$A_R[t] = \zeta \cdot S[t] \cdot R_\Sigma, \quad (4.9)$$

$$B_R[t] = \eta \cdot R_\Sigma, \quad (4.10)$$

$$R_\Sigma = \sum_{k=R_S+R_0}^{\min(t, R_E)} N_R[k]. \quad (4.11)$$

To calculate  $R_\Sigma$  I sum the number of rioters over a window  $W_R$ . The window  $W_R$  initially runs from the iteration during which the riot started  $R_S$  to the current iteration  $t$ . Once the riot has stopped the window is capped at that iteration,  $R_E$ . For each successive iteration, the start of the window is brought forward by a single step, such that the start of the window can be described as the sum of  $R_S$  and  $R_0$ .  $R_0$  is defined as the number of iterations the riot has stopped. Reducing the value of  $W_R$  allows the number of police officers to return to their normal state before the riot, with amplitude  $A_0$  and baseline  $B_0$ .  $B_R[t]$  is determined by multiplying the past riot activity  $R_\Sigma$  and a fitted parameter  $\nu$  (Equation 4.10).

$A_R[t]$  is calculated in a similar manner and features a fitted parameter  $\zeta$  (Equation 4.9), but also a time dependent sensitivity function  $S[t]$  (Equation 4.12):

$$S[t] = 1 + \theta * \frac{e^{\kappa \cdot t - \lambda}}{1 + e^{\kappa \cdot t - \lambda}}. \quad (4.12)$$

As the riot ages, the severity of the situation increases and therefore there is an increasing need for the police to contain the riots. I describe this effect by including the sensitivity function  $S[t]$ , which is a sigmoid function increasing with time.  $S[t]$  contains three parameters: the total increase in sensitivity  $\theta$ , and two time control parameters  $\kappa$  and  $\lambda$ .

## 4.3 Methods

### 4.3.1 Contact Network

The contact network between the agent that is used in the gathering phase is generated by the Block-Two Level Erdős-Rényi (BTER) model [94]. I use this model to generate networks that resemble to real world human contact networks, with features like community structure and heterogeneous degree distributions [167]. Generally there are two approaches to use networks in numerical models; the first is to use a real world empirical network based on data, the second is to generate a network using an algorithm. In the first approach, the network that is used is fixed, and the numerical model has to be matched to the existing network. In my model this would mean that the number of agents is dependent on the available data, i.e. the number of nodes in the network. This approach is relatively inflexible, as adding or removing nodes can violate the specific network properties of the system that is under investigation. The second approach is to use an algorithm that can generate a network. Often these algorithms are designed to create networks with specific properties, for example random or scale-free degree distributions. These algorithms can generate networks with such properties at any desired scale, resolving the problem from the first approach. The main downside of this approach is that many of the types of networks that can be generated only have one or two of these specific properties, and hence are often used as simplifications of real world networks in the cases where these properties match.

The BTER model that I use in this chapter marries the two approaches, by taking two key descriptors of real world networks, and then generates networks with the same features at the desired scale, thus allowing me to create a realistic social network structure for the agents. The two necessary descriptors are 1) the network degree distribution and 2) the clustering distribution. The degree distribution describes the frequency of an agent with  $k$  connections to other agents. The clustering distribution is a distribution of the local clustering coefficients for each degree. The local clustering coefficient describes how close the vertices to which a vertex is connected are to forming a complete graph [211].

### 4.3.2 Model Initialisation and Parameterisation for the London 2011 Riots

I apply the model to three London boroughs during the riots in 2011, modelled as independent locations. To apply my model, which is based on general concepts, to these locations I have had to include more parameters than simpler models like the Epstein model [55]. Half of these parameters are designed to be set according to the data relating to the riot under investigation. The number of parameters left open for interpretation is similar to the number of parameters in simpler models. In total the model has sixteen parameters that require values to initialise a calculation: a) two controlling the pre-riot gathering; b) seven influence how agents join and leave the riot; and c) the remaining seven are associated with the police response algorithm. Some parameters can be specified using properties derived from data collected from a specific riot (e.g., the number of police officers present at the start of the riot). For other parameters I use the model to heuristically fit them to the data. The parameter values for my model configuration are listed in Table 4.1.

Symbol	Description	Units	Haringey	Enfield	Croydon
$N_G$	Gathering Size*	Agents	300	0	0
$\alpha$	Persuasiveness	Unitless	0.1	0.1	0.1
	Riot start time*	Hours	20	43	65
$N_{R0}$	Riot start size	Agents	20	10	50
$\beta$	Network control 1*	Unitless	0.2	0.2	0.5
$\gamma$	Network control 2*	Unitless	5	5	5
$\delta$	Deterrence	Rioters/Police officers	11.9	11.9	11.9
$\varepsilon$	Fatigue	Unitless	0.13	0.13	0.13
	Cooldown	Hours	14.5	14.5	14.5
$A_0$	Initial amplitude*	Police Officers	60	90	130
$B_0$	Initial baseline*	Police Officers	30	40	60
$\eta$	Amplitude sensitivity	Unitless	$7 \cdot 10^{-6}$	$7 \cdot 10^{-6}$	$5 \cdot 10^{-5}$
$\zeta$	Baseline sensitivity	Unitless	$2 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$
$\theta$	Sensitivity increase	Unitless	50	50	50
$\kappa$	Sensitivity increase time control 1*	Unitless	0.075	0.075	0.075
$\lambda$	Sensitivity increase time control 2*	Unitless	12	12	12

**Table 4.1: Model parameter values used for model calculations.** *Values based on data are marked by an asterisk.*

I initialise the model with ten thousand agents that each has a hardship level, a physical age, and use a common social communication network. Hardship levels are assigned using a uniform distribution  $U(0,1)$  [48, 55, 198]. I use an age distribution

for the agents based on demographic data for London [200]. I restrict my study to agents aged between 13 and 65 years, based on the Home Office and Ministry of Justice arrest records from the London riots that show that the contribution from other ages is negligible [18, 164].

To generate the communication network between the agents using the BTER model [94] I take the degree and clustering distribution from a real social network [167]. The data from this network is based on an online social network like Facebook and Twitter. The reason to use this network is that the underlying structure is supposedly very close to real world human contact networks. The network was generated as part of the WIW project in Budapest, Hungary [167], with the general aim to map out social acquaintance among friends and family. As such, the network was invite-only, such that new members could only be added through invites from existing members. Additional links between existing members can also be added, if agreed upon by either party. The study that presents the network claims that the structure is representative of a real world human contact network, in part due to the very limited use of pseudonyms and the general encouragement to use real names. Additionally due the relatively short age of the network, newly formed links between people in the real world have a minimal structural effect. About 90% of the participants do not use the additional message board and messaging services, suggesting that the links represent genuine pre-existing social acquaintance. The reason to use this network over larger networks like Facebook and Twitter is that active users of Facebook and Twitter often have an very large number of connections, much higher than the actual count one would consider 'friends' [218]. Additionally these networks also have a large number of inactive users with a minute number of connections [218]. Lastly, it turned out that for the London riots, Blackberry Messenger was the preferred method to spread and communicate information [15, 75], of which the underlying structure is much closer to an offline acquaintance network than online social media like Facebook and Twitter.

I also use the BTER model to structure the age of the agents in the network, making it more likely for agents to have similarly aged contacts. The BTER algorithm consists of two different stages: 1) the nodes in the network are divided into clusters, groups of nodes, that are highly interconnected; and 2) the connections between these clusters are added. I achieve this by grouping 80% of the agents into the clusters by age so that agents are more likely to be connected to others with a similar age. To avoid agents only having connections with agents of a similar age, I distribute the remaining 20% of agents by assigning them a random age weighted by the age distribution from

### 4.3 Methods

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the study region.

In my model a riot is preceded by a gathering. For the Haringey borough, I set the gathering size  $N_G$  to 300 based on a news outlet report of the protest [54]. I assume a gathering size of zero for the other two boroughs, Croydon and Enfield, as there were no protests or other forms of gatherings reported before the riots in those boroughs broke out.

After the gathering phase the riot is initiated at the same time as observed in the real world. The starting times of the riots are obtained from the Metropolitan Police Service (MPS) report [121]. The riot start size  $N_{R0}$  is set experimentally for each borough to match the caller activity from the data. The process for setting the parameters that are not based on data is described towards the end of this section. After the riot starts agents can join or leave the riot at every 30-minute time step for the eight days in the model. The model runtime exceeds the duration of the London riots to investigate whether the model predicts the correct riot duration.

The two parameters  $\beta$  and  $\gamma$  from the additional motivation  $M_C$  are set to match the mean degree and variance in degrees in the communication network between agents. The three remaining parameters  $\delta$ ,  $\varepsilon$  and the cooldown period are not informed by specific data. The value of  $\varepsilon$ , the rate at which an agent experience fatigue due to participating in the riot, and the cooldown period relate to physical properties of the agents and are therefore bound in the range of values they can take to prevent unrealistic situations. I simplify further by setting a single value for these parameters for all agents rather than assigning them individually.  $\varepsilon$  is then chosen such that after roughly three hours of rioting the agent would have a probability of  $1/2$  to leave the riot in the absence of police forces. The cooldown period for Haringey is different from Enfield and Croydon to provide a better fit (Table 4.1). The difference between the two cooldown periods however is minimal, as they are only one iteration (30 minutes) apart from each other.  $\delta$ , the deterrence, is set to match the data, just like the riot start size. Of the 9 parameters listed in the pre-riot gathering and the riot stage 5 are set according to data, and 4 are set otherwise.

The initial number of police officers in each borough is set according the MPS data [122] prior to the start of the riot. The parameters  $\kappa$  and  $\lambda$  relate to the increasing sensitivity of the police to riot behaviour. They are set to match the starting time of the riot activity in Haringey. The values of  $\kappa$  and  $\lambda$  are the same for all three boroughs, since riots in one borough will likely also raise sensitivity in other boroughs. The

three sensitivity parameters  $\eta$ ,  $\zeta$  and  $\theta$  are set through model analysis. Before using the police response module I used the MPS data on the number of police officers to drive the agents decision to join and leave the riot. This allowed me to obtain a range of values for the number of rioters, on which I based the values for  $\eta$ ,  $\zeta$  and  $\theta$ .

The parameters that are not drawn from data are set manually through model analysis. This includes the parameters for the riot start size  $N_{R0}$ , the persuasiveness  $\alpha$ , the deterrence  $\delta$ , the fatigue  $\varepsilon$ , the cooldown time, the amplitude sensitivity  $\eta$ , the baseline sensitivity  $\zeta$ , and the sensitivity increase  $\theta$ . I sort the parameters into two groups, those that relate to the behaviour of the rioting agents and those that relate to the behaviour of the police response. The values of the parameters are set in two different stages, based on the different parameter groups.

I first set the values of the parameters that influence the agent behaviour. I decouple the riot and police behaviours in the model, by replacing the police response algorithm with the data on the number of active police officers during the unrest in London [122]. This approach reduces the interactions and dynamics in the model, making it simpler to set the parameter values such that the number of active rioters in the model matches the observations from the number of callers from the data. I first change the values of the riot start size and the police deterrence to obtain the correct duration and the number of episodes. By letting the riot run longer than the data, I can check if the riot in the model does not continue beyond the time in the data. The fatigue rate and cooldown time influence the periodicity and the start time of the riot for each day, and are also bound by the physical interpretation. The initial value for the cooldown time for example was 24, corresponding with a 12 hour stop of any riot activity after leaving the riot. After obtaining a general match for the duration, number of episodes, periodicity and start time of unrest at each day I further fine-tune the values of these parameters to match the general trend in the daily peak caller activity, the relative decrease in these peaks, and the times at which the maximum caller activity occurs.

In the second stage I set the values for the parameters that relate to the police response. Similar to the first stage I decouple the interactions between the police and the rioters in the model. Instead of replacing the number of rioting agents by the caller activity from the London riots, I use the agent behaviour (number of rioters) that I obtained in the first stage. The police response in the model already has the correct periodicity, as the parameters from the underlying sinewave are drawn from data on the London riots. The remaining daily minimum (baseline) and daily variance

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(amplitude) are set through the remaining parameters  $\zeta, \eta$ , and  $\theta$ . I first set the baseline sensitivity  $\zeta$ , to obtain the correct minimum amount of police officers for each day. Lastly I vary  $\theta$  and  $\zeta$  together to match the daily amplitudes in the number of active police officers, and the general increasing trend.

The approach to decouple the interactions between the rioters and the police in the model and replacing either by static behaviour makes it possible to set the parameter values correctly. I found that without this approach, small changes in parameter values, especially when changing two or more at the same time, would result in drastic behavioural changes in the model. Temporarily reducing the dynamics between the rioters and the police made it considerably easier to choose parameter values that resulted in the same general behaviour as observed in the data from the London riots. As the model is stochastic, (re)linking the two systems in the model does not necessarily always lead to the same behaviour of the two solitary components combined. In some cases I therefore also had to make small adjustments after recombining the agents and the police response in the model. A sensitivity analysis for the parameters that are not based on data is described in Appendix 8.5, which I conducted after I arrived at the values shown in Table 4.1.

### 4.3.3 Model Evaluation

To develop and evaluate the model I have used data from the Metropolitan Police Service (MPS) [122]. These data include the number of calls made to the MPS, the number of arrests and the number of police officers on duty for the period 6–10th August, 2011. All data are available per hour per borough. The number of police officers in a borough represents the number of active police officers that belong to that borough unit under normal circumstances, but there is no guarantee from the MPS that these police officers have not been despatched elsewhere to aid in surrounding boroughs.

I distribute the ages of the agents in the model according to the age distribution of the population of London, available on [200]. The degree and the clustering distribution for the BTER model are based on data from real world social networks [94, 167]. Other data I use to help formulate the model are the arrest data hosted by the Ministry of Justice and Home Office available on [164], and the distribution between offenders home location and location of offence [18].

To compare the riot model output to the caller activity during the London riots I calculate the median value at each iteration from the ensembled runs to create a 'median run'. I opt for the median over the mean because the mean gives a skewed representation of riot duration when nearly all of the individual runs have already ceased riot activity. The median keeps reporting positive values for riot activity until the last individual run has stopped.

To account for the stochasticity in the model I run the model 1,000 times with the same parameter settings to obtain an ensemble of behaviours. For each individual run I calculate the total police and riot activity, the riot duration, and the peak police and riot activity. The total riot and police activity are calculated as the sum of the number of rioters and police officers over all iterations. For all these metrics I obtain the mean, median and variance to compare different parameter settings.

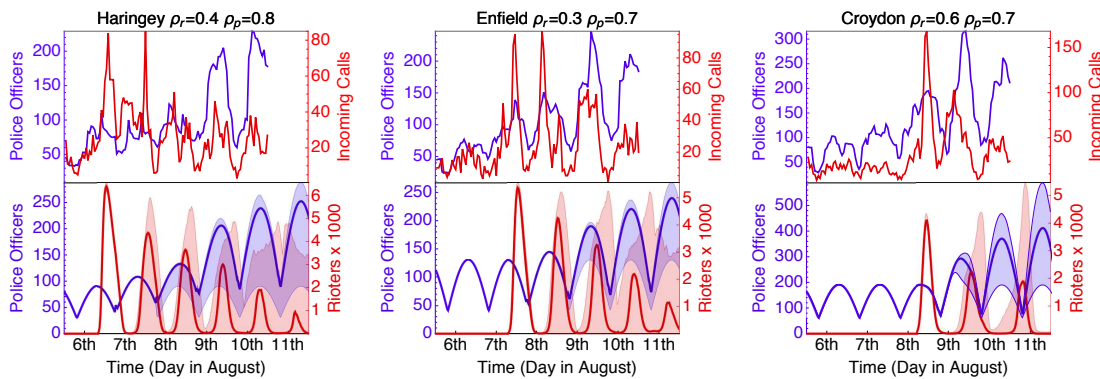


## 4.4 Results

### 4.4.1 Evaluation of the Model Control Experiment

I evaluate my model by comparing predictions to data available from the MPS for August 6–10, 2011. In particular I compare the number of police officers actively deployed during that period and the number of incoming calls with the estimated number of police officers and the number of rioters. I link caller activity with the timing of the riot outbreak within each London borough using data from the MPS report on the London riots [121].

The model reproduces the observed trend and daily cycle in the number of callers within each London Borough. Comparing the predicted number of median rioters in the model with the number of callers results in Spearman's rank correlations  $\rho_r$  between 0.4 and 0.6. Table 4.2 lists both the Pearson and Spearman rank correlation coefficients in more detail for all three boroughs for both the number of rioters and police officers. The riot outbreaks in the model coincide with the observed peak in caller activity (Figure 4.2). The model also reproduces the changing number of police officers on active duty during the riot period ( $\rho = 0.7$ – $0.8$ ).



**Figure 4.2: Model and observed riot activity for Haringey, Croydon, and Enfield in London, August 6–10, 2011.** I model riot activity (number of rioters) as a proxy for the MPS observed number of incoming calls. The police response is shown in blue, and the number of calls and rioters in red. The solid lines in the bottom row denote the median value of an ensemble of 1,000 individual model runs and the shaded envelope represents the ensemble range.  $\rho_p$  describes the Spearman's correlation coefficient between the data on the number of police officers and model output (blue), and  $\rho_r$  is the Spearman's correlation between the number of callers and the modelled riot activity (red). Appendix 8.6 shows a direct overlay of the data and the model behaviour.

The data show that the number of police officers and the number of calls share the same diurnal cycle, although the peaks and trends of these are not the same. The diurnal cycle for the number of police officers is exogenously driven by the underlying sine wave, whereas the cycle for the rioters is a combination of the interaction between the police and the rioters through the repression  $R$ , and the cooldown time and fatigue rate of the agents. Both the number of rioters and police officers have daily minima at 0600. Peak riot activity, as informed by the number of incoming calls, occurs between 2200 and 0000, consistent with observations of other riots [120]. These features are captured by the model. However, the number of police officers deployed to the street generally show afternoon and late evening peaks, presumably reflecting changes in work shift cycles and responses to elevated riot activity in the evening. The second and larger peak relating to the riots is captured by the model.

**Table 4.2: Correlation table.** *Spearman and Pearson correlation coefficients for 2011 London riots data and model behaviour for three boroughs of Haringey, Enfield, and Croydon in London. The number of rioters in the model is compared against the number of incoming emergency calls, and the number of police officers in the model is compared to the number of active police officers on duty.*

	Pearson	Spearman
<b>Riot</b>		
Haringey	0.51	0.38
Enfield	0.19	0.26
Croydon	0.59	0.56
<b>Police</b>		
Haringey	0.92	0.83
Enfield	0.47	0.69
Croydon	0.81	0.74

#### 4.4.2 The Influence of Pre-Riot Gatherings and of Initial Riot Size on Ensuing Riot Activity

Pre-riot gatherings such as protests and demonstrations can help to establish a group identity and thus may influence riot dynamics [92, 184]. The size of the protest, for example, may indicate the level of support for the common cause and give individuals the confidence to eventually join a riot. My model includes a numerical description of such a gathering and is described further in the Section 4.2. I use the Haringey riots

## 4.4 Results

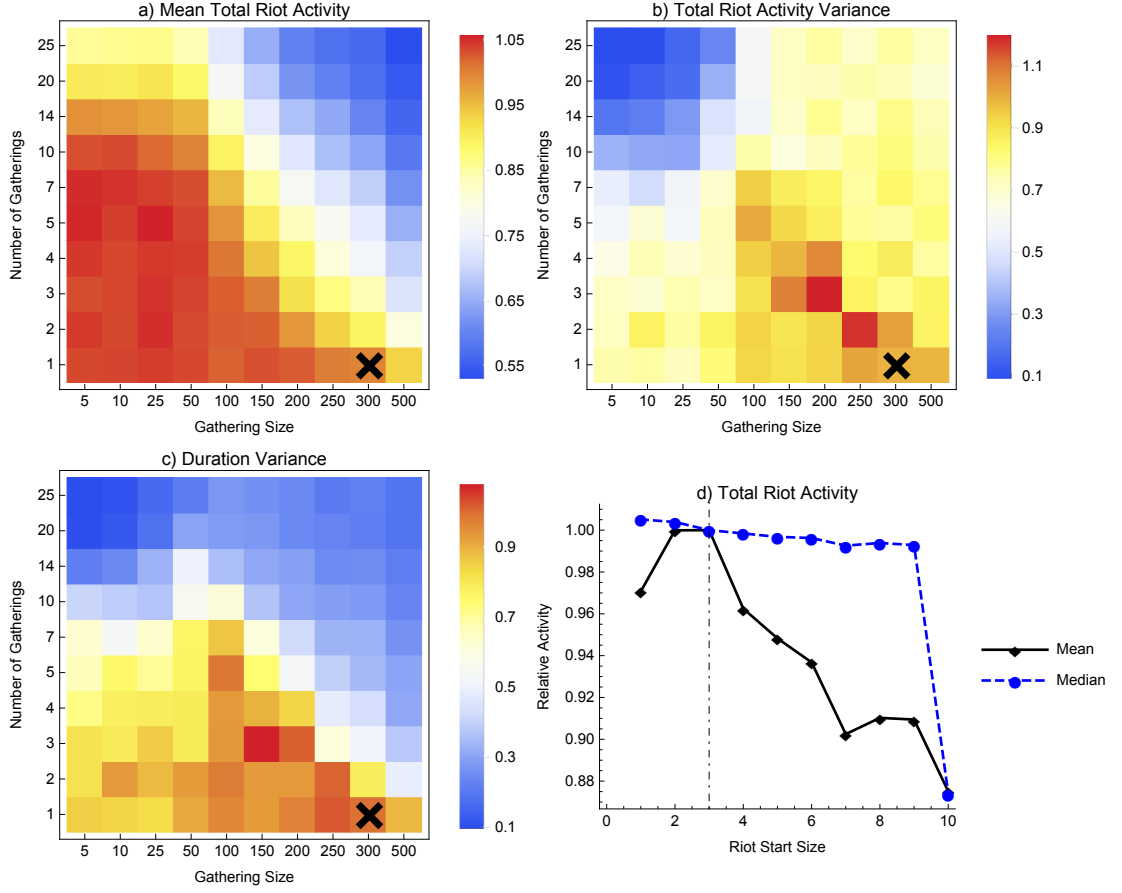
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as a test-bed to understand how different initial conditions could lead to different outcomes and riot activity. The civil unrest in Haringey during the 2011 London riot was preceded by a largely peaceful protest.

The control experiment for the Haringey riots initialises a single gathering with 300 agents before a subgroup then initiates a riot (Table 4.1). To evaluate the influence of the gathering on the riot I vary the size and frequency of the pre-riot protests. I also investigate the effect of different riot start sizes to get a better understanding of how initial conditions result in different riot behaviour. I define the mean total riot activity as the sum of the number of rioters over time averaged over 1,000 model runs.

Figure 4.3a shows that larger and more frequent gatherings lead to lower mean total riot activity. These enhanced gatherings lead to elevated levels of hardship, which represents the internal motivation of agents to join a riot in the model. During the gathering agents can influence the hardship of other agents through communication. Larger gatherings can motivate a larger subset of agents to start the riot. However, the larger initial number of rioters attracts a larger number of responding police officers that in turn discourages further rioting through the repression  $R$ , which is common to all agents (Equation 4.5). The outcome is a shorter riot with less overall activity. Another reason for the decrease in mean total riot activity is associated with the initial size of the riot. A large number of agents joining riots also means that a large number will leave at the same time, according to their individual endurance clocks. Agents have an embedded fatigue or endurance clock that prevents them from participating in the riot indefinitely. This mechanism also makes agents more likely to leave the longer they stay in the riot. When a cohort of agents joins at the same time, they will leave at approximately the same time due to their synchronized endurance clocks. This synchrony among rioting agents when they leave the riot decreases the ratio of agents to police officers for agents left in the riot, making them more likely to leave and discouraging others from joining. The opposite effect happens when the police initially deploy only a small number of officers: a lower deterrent causes more agents to join the riot (Figure 4.4a and b). The agent strategy to achieve the highest riot activity in the model would be to sustain effort over time to prevent the number of rioters dropping below a certain threshold beyond which efficacy is low and the riot subsides due to agents leaving and not returning. These results highlight the value of better understanding the relationship between pre-riot activities and the probability of riot formation.

Figure 4.3a also shows that the mean total riot activity is insensitive to a wide



**Figure 4.3: Sensitivity analysis for riot activity and duration for different parameter settings relative to the Haringey control run.** a) and b) and c) show the sensitivity in mean riot activity, riot activity variance and the duration variance to the number of gatherings and gathering size before the riot. d) shows the sensitivity of the mean and median riot activity to the riot start size. The Haringey control simulation (Figure 4.2) is denoted by a cross in a)–c) and by a dash-dotted vertical line in d).

range of values for the number of gatherings (e.g., one to ten) and the gathering size (e.g., one to fifty). Larger values for the variance between simulations with the same parameters are generally associated with less frequent, larger pre-riot gatherings (Figure 4.3b and c). There is less variance in riot activity when pre-riot gatherings are smaller and more frequent because of the gathering mechanism: multiple rounds of small gatherings create clusters in the network where hardship levels are elevated, effectively representing a strongly shared group identity. These clusters of elevated hardship results in the same group of agents to be selected for the riot for every model run so that the associated variance is much lower than for model runs without such strongly localised hardship structures in the network.

## 4.4 Results

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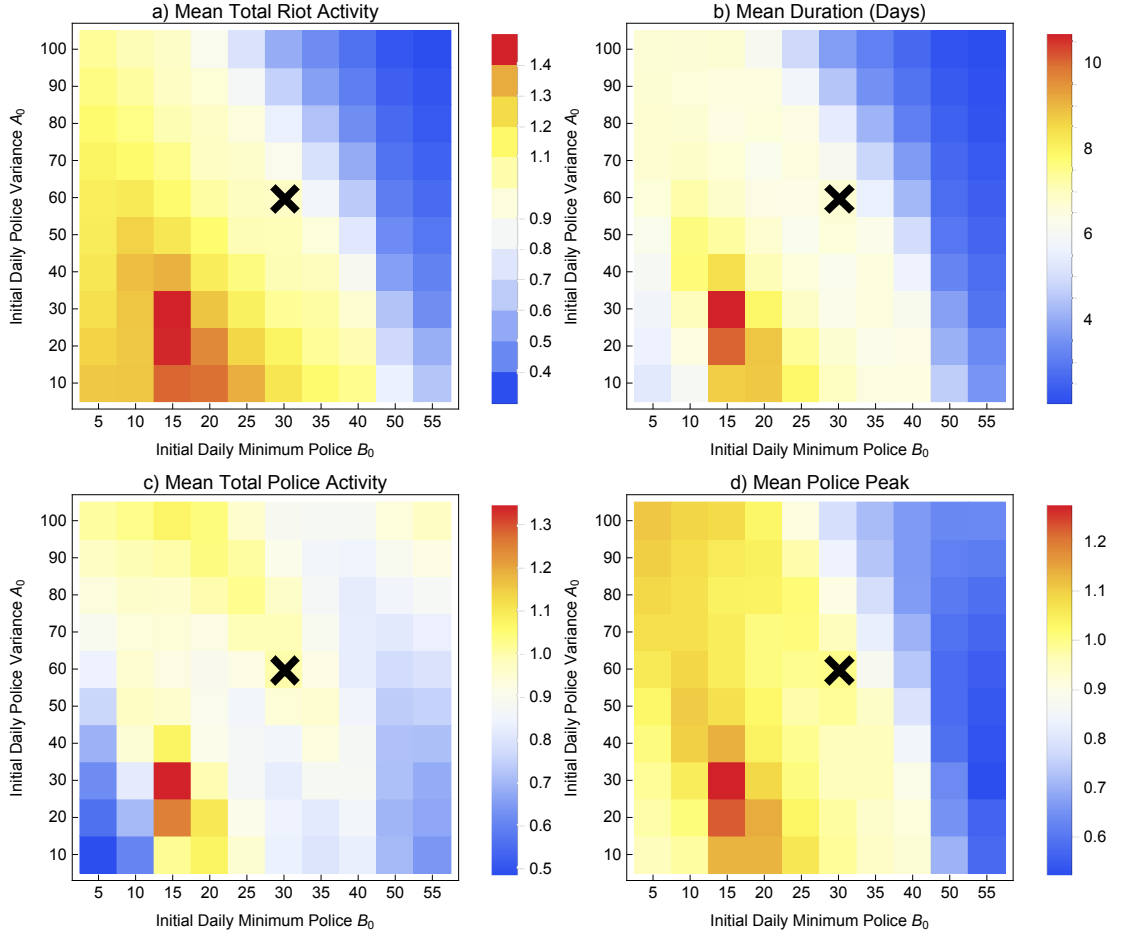
Figure 4.3d, associated with the control gathering size of 300 agents, shows that increasing the initial size of the riot has little effect on the mean total riot activity up to an approximate threshold of 50 rioters beyond which there is a precipitous drop in the riot activity. The median values for riot activity are less affected by changes in the riot start size and generally decline more slowly. The difference between the mean and median values reflects the large range of possible riot scenarios described by the probabilistic ensemble of model runs that include a few extreme scenarios associated with large initial riot sizes that attract large police presence and a short riot duration.

### 4.4.3 Role of Police Response and Riot Dynamics

As reported above, more police prior to the start of the riot leads to less total riot activity and shorter riots (Figure 4.4a and b). Figure 4.4c and d show that adopting this strategy to contain the riots reduces the mean total police activity and the mean police peak over the duration of the riot. An extremely low number of police officers at the start of the riot also reduces riot activity and duration, due to the aforementioned increased synchronicity in agent behaviour. This effect is shown in the lower left corners in the panels a) and b) of Figure 4.4, where less police first leads increases riot activity and duration, and then to a decrease. If there is virtually no police present there is no deterrent effect, thus letting the agents join at the same time. Because of the synchronised endurance clocks, the agents become very likely to leave at the same time, ending the riot relatively early.

In the original control experiments I assumed that the police have perfect knowledge of the current state of the riot and that they have the resources to adapt as the riot progresses. In practice, neither the police nor the rioters know with certainty the number of rioters that are present. For instance, during the London riots the MPS suffered resource shortages in the first three of five days of the riot [121]. To evaluate the effect of incomplete knowledge of the number of rioters I introduce uncertainties associated with the riot dynamics. I scale the perceived riot size by the police with a Gaussian distribution with mean  $\mu$  and standard deviation  $\sigma$ . I increase the number of runs to 10,000 to capture the wide range of behaviour introduced by the increased stochasticity on the rioter-police feedback.

Figure 4.5a shows that underestimating the riot size by the police causes the mean total riot activity to increase. A riot size underestimate of 20% causes a 5% increase in mean total riot activity compared to the control run. The variance in

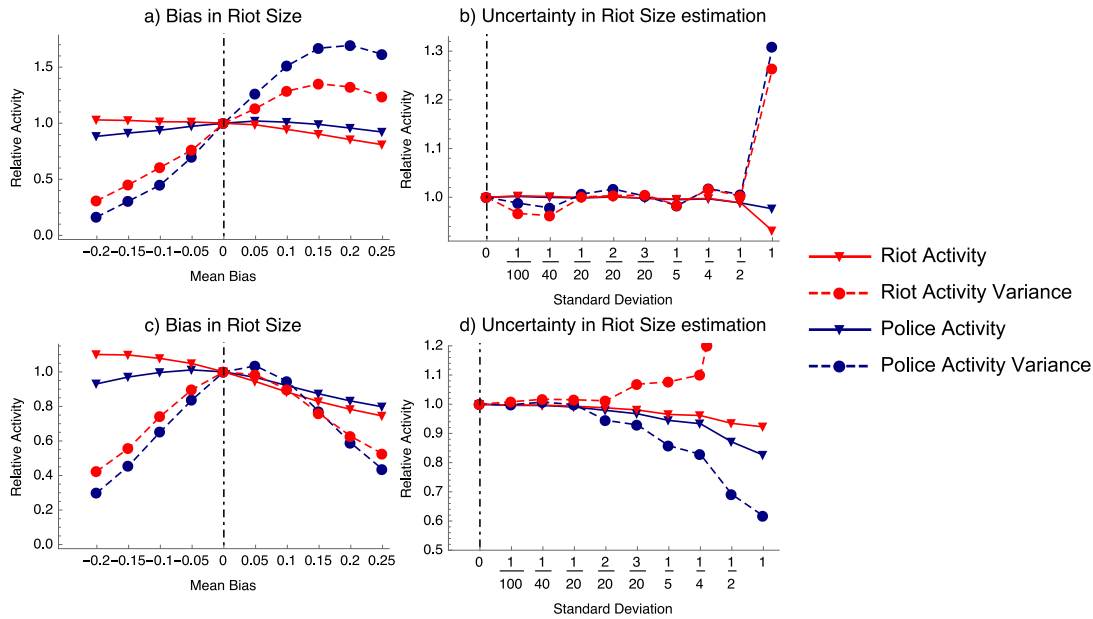


**Figure 4.4: Model sensitivity to initial number of police officers for mean total riot activity a), riot duration b), total police activity c), and police peak d).** *The Haringey control simulation is denoted by the cross. The model metrics are expressed relative to the Haringey control simulation except for b).*

riot activity decreases with an increasing level of underestimation of the riot size, suggesting that a weaker police response results in a higher probability of a large riot. Figure 4.5a also shows that overestimating the riot size initially increases the police activity but ultimately reduces the riot activity and the total amount of necessary police officers. The increased police response caused by the overestimation of riot size has the potential to end riots earlier, introducing more variance in riot duration and total riot activity and therefore also total police activity.

Figure 4.5b shows that introducing the police uncertainty in riot size does not significantly change the mean total riot activity or the total police activity except for very large levels of uncertainty. This is because of my initial assumption that the police update their knowledge of the riot size every 30 minutes. This means that while their

## 4.4 Results



**Figure 4.5: Relative mean total riot activity (solid blue), mean total police activity (solid red) and associated variance (dashed) for bias and uncertainty in riot size estimation.** Noise is added to the estimated riot size used for the police response in the form of a Gaussian or normal distribution. The bias refers to the mean of this distribution, the uncertainty to the standard deviation. In panel a) and b) the police estimate the riot size every time step (30 minutes), in panels c) and d) the police estimate the riot size every 12 hours. Riot activity and variance are relative to the Haringey control simulation denoted by the vertical dash-dotted line.

estimation of the riot size can be inaccurate at any moment in time, it tends to be correct on average over multiple hours and any gross mistakes will be limited in time. In practice, the police may not be able to gauge so rapidly the changes in the number of rioters and so I ran another set of simulations with an increased lag in the time at which the police evaluate riot size.

The effect of reducing the frequency at which the police evaluates the riot size is shown in shown in figure 4.5c and d. To describe a more realistic situation I reduced the update frequency to 12 hours rather than every time step. Figure 4.5c shows a similar pattern for the mean total riot and police activity as Figure 4.5a, except that the police activity now reduces instantly as a result of overestimation. Each estimate of the riot size has a longer persistence time so that overestimation has a larger effect on the riot activity therefore reducing the amount of necessary police officers and variances in riot and police activity.

Figure 4.5d shows that increasing the uncertainty about the riot size now causes

a small but steady decline in the total riot and police activity. I find that the decline in riot activity is not necessarily positive because there is a greater increase in the variance in riot activity at higher levels of uncertainty. The decline occurs because of the times at which police initially overestimate the riot size and suppress the riots entirely very early as a result. The increased variance however highlights that a significant proportion of riots effectively escape police control. Large mistakes in assessing the size of the riot will last for 12 hours and consequently will lead to a wider range of possible riot outcomes. Such mistakes can either end the riots earlier in case of overestimating the riot size or can lead to a shortage of police resource and longer riots in the case of underestimating the riot size. The variance in police activity declines as a result of the increased uncertainty. Once the riot is over the number of police officers returns to normal levels. The uncertainty about the riot size increases the potential to end the riots earlier, therefore also synchronising the number of police officers earlier across multiple runs, ultimately reducing variance in police activity.



# 4.5 Discussion and Concluding Remarks

I showed using an agent-based model, linked with a realistic social network structure, that my model can capture the macroscopic dynamics of the rioter-police relationship during the London 2011 riots (Figure 4.2). The motivation of an agent to join the riot in my model is based on general principles that could be associated with any riot. The simplicity of the model allows me to explore a large ensemble of realisations so that I can report probabilistic values for riot dynamics. Guided by social theory, I have included a description of a pre-riot gathering and have shown this step is crucial for understanding the intensity of the riot. The agents in my model exhibit a simple form of implicit collective identity [92, 184], parameterised using the communication network, which develops with successive pre-riot gatherings. I showed that the size and frequency of pre-riot gathering and the initial police response has a significant influence on the total riot activity; and consequently economic costs when attaching some monetary cost to a unit riot activity.

I chose to develop the model using general concepts to describe a specific riot so that I could eventually use the same model to describe contrasting behaviour of other riots; for example, characterized by different social network structures. If such a model can exhibit multiple types of behaviour it would become an effective generalized tool for understanding what local factors drive riot dynamics. Towards that generalized model, I have developed a description of pre-riot protests to help explain the differences between riots. The protest establishes the initial conditions for the riot, and allows me to investigate how these initial conditions are determined through such gatherings. I have also developed concepts such as agent fatigue rates and cooldown periods, allowing me to reproduce observed periodical behaviour of riot activity that can be sustained over multiple consecutive days. Previous studies have implemented jail time after arrest [55, 198], which has the same effect as my cooldown concept but is only applied to agents that get arrested. I did not include agents being arrested because my proposed mechanisms could already reproduce MPS records during the London 2011 riots [122]. Moreover due to the shortage of police personnel during the start of the London riots the actual number of arrests remained very low, until later more police officers were made available [121, 122].

My control model calculation captures the majority of the observed riot activity in the three boroughs I examined ( $p_r = 0.4\text{--}0.6$ ) in London between the 6th and the 11th of August 2011. This model performance can be improved by only considering

the intervals during which there is riot activity instead of multiple 24-hour periods. For example, I found that the relatively low correlation for Enfield ( $\rho_r = 0.3$ ) is due to the anomalously high peak number of incoming calls on the morning of August 8th, which is not captured by the model. Given my knowledge of the timing of riot activity, these calls are likely to be related to damages caused by the riot the previous evening. Moreover for the Croydon borough, the three days prior to the start of any local riot activity (August 8th) are also taken into account for the correlation. The high correlations for the number of police officers ( $\rho_p = 0.7-0.8$ ) are mainly determined by the ability of the model to capture the shape of the daily cycle.

A direct comparison of my model to previous studies of riots and civil unrest is non-trivial. Some previous studies did not validate their model with data [24, 25, 28, 55, 86, 103, 104, 129, 198], while others that did compare their models against data only predict the volume of events and provide insufficient details about the chronology and how events differ from each other [31, 100]. A previous model analysis of the 2011 London riots [48] includes a time series of the number of offenders, police officers and recorded crime during the London riots, but only compares the predicted residential location of rioters to the available data. This study also focuses on a typical night instead of describing the multi-day nature of the London riots. Other studies on the London riots use statistical modelling to predict diffusion of riot activity to other sites [17], the volume of riot-related offences in local areas [16] and other variables including target choice [18].

Through sensitivity analyses of the pre-riot protest size and frequency I found that frequency has a larger impact on riot behaviour than size. Several small gatherings preceding a riot cause a precipitous drop in variance of the expected level of riot activity and duration (Figure 4.3) making riot behaviour much more certain. These repeated small gatherings create localised areas of elevated hardship in the social network, which implicitly simulates a collective identity between agents. The action of an agent joining the riot is a self-exciting process [128], as it becomes more probable that other agents will join as the riot size grows. The collective identity strengthens the local support between agents to join the riots and makes them join as a group rather than as individuals [119], reducing the variance.

I also showed that multiple large protests lead to a larger riot start size in the model. Despite the larger initial size of the riot, the total cumulative riot activity decreases due to an increased police response that contains the riot (Figure 4.3). In practice, police activity is finite with large-scale responses delayed due to importing

## 4.5 Discussion and Concluding Remarks

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police officers from outside the immediate region. For example, during the first few days of the London riots the MPS were stretched for resources so that a larger protest or larger group of people initiating the riot might not have resulted in a quicker resolution of the riot [121]. Conversely, I showed that a greater initial police presence can help to decrease the expected riot activity (Figure 4.4), resulting a smaller cumulative police resource over the entire riot period. Likewise, crowd size is generally used to assess the threat of a demonstration so that large demonstrations are usually met with a large police response. But this strategy is not always optimal: the outbreak of violence from a demonstration is often the result of the interaction between police and protesters, and the aggressiveness of the police response is positively related to the crowd size [115, 120]. So, an initially large police presence at a protest could increase the chances of civil violence rather than lead to a quick resolution. Many protests remain peaceful however as there are many other factors that might affect the outcome of a police response, including for example the subject of the protest. Another factor that impacts the effectiveness of the police response is the accuracy of information about the size and the number of riots (Figure 4.5). I showed that frequently assessing the riot size can help reduce riot activity even if there is great uncertainty about the situation.

In this work, I developed a model that describes riots within multiple individual London boroughs. This is a first step towards developing a model that can be generalized for the whole of London and describes the flow information across multiple geographical locations and social networks. A key future model development will involve the inclusion of online social networks and multiple coupled riot sites, to describe how a riot in one location spreads in time and space, and explore the impact of modern social media.

# CHAPTER 5

## Segregation and Networks: When do Riots Spread?

### ABSTRACT

Some civil disturbances can be traced back to a single *trigger event*. The potential violence following a trigger event is dependent on the spread of disorder from one location to another. The 2011 Arab spring for example started after the self-immolation of a civilian in Tunisia as an act of protest, and eventually led to widespread violence across North-Africa and the Middle-East. This leads to the question of why an event in a remote location incites violence over other and much larger geographical areas. To answer this question I introduce a new general mechanistic agent-based model of civil violence. I describe separate abstract issues about which the agents can be aggrieved, and study how the relationship between these issues, structural differences in grief between communities, and interconnectivity between different agent clusters in the network influence the probability of riot spread. I find that there is a minimum number of connections between communities that enables riot spread, characterized by a critical transition. Moreover I find that small amounts of segregation between groups promotes riot activity and facilitates transmission from one location to another. Lastly I find the conditions under which a riot can spread through potential riot locations to other areas, without the intermediary locations experiencing outbursts of unrest.

**Author Contributions:** This chapter was written by Jelte Mense, with editorial contributions from Paul Palmer and Matthew Smith.

# 5.1 Introduction

Some demonstrations and riots can be traced back to a single event, a so-called *trigger event*. For example the event largely believed to be the trigger of the 2011 Arab spring was the self-immolation of a civilian in Tunisia [61]. This act catalysed into protests, riots, and revolutions across many countries in North-Africa and the Middle-East [63]. Likewise instances of (perceived) police violence against minorities in the last decade in Europe (e.g. Paris 2005, London 2011, and Stockholm 2013 [161, 170, 171]) and recently in the USA (e.g. Ferguson 2014 & Baltimore 2015 [189, 190]) led to demonstrations and riots that spread to multiple large cities. However these trigger events were not unique: similar acts of police violence against civilians happen more often, but do not escalate into outbursts of civil violence. This leads to the question of why some events incite violence that spreads out to multiple locations, and others do not.

The potential violence following a trigger event is in part dependent on the spread of unrest from one location to another. What separated the 2011 Arab spring from other instances of conflict, was how unrest spilled over to neighbouring countries, eventually encompassing the majority of North-Africa and the Middle-East [20, 64]. Likewise the Metropolitan Police Service (MPS) during the 2011 London riots were not only surprised by the ferocity of the demonstrators who started the riot, but also by the overwhelming rate at which the riots spread to other boroughs in London, leaving the MPS with too few resources to deal effectively with the riots during the first few days of the unrest [161]. Understanding why and under which conditions trigger events cause unrest to spread to other locations can potentially help in detecting and addressing underlying problems, and possibly limit or help prevent the escalation of violence within and between communities.

Previous studies have attempted to explain under which conditions collective action emerges using economics and rational choice frameworks [118, 142]. In these studies the individual motivation for the participation in a collective action is described as a combination of potential (monetary) benefits and costs, where individuals are more likely to join when there is a net positive gain. The costs are described as a function of the risk of participation. Possible risks from participating are for example getting arrested or injured [111]. The benefits are described as individual and collective goods, such as the potential societal change that will improve a specific groups situation [137]. However, such approaches have not been able to demonstrate

basic behaviours often displayed in riots, such as looting [118].

Focusing on the individual and its relation to the group, theories from social psychology have resulted in a framework that describes the motivation of individuals to join in events of social unrest, facilitating their spread. The three major components theorised to drive individuals to join in protests are: 1) *Collective identity*; 2) *Emotions* derived from (group-based) injustices; and 3) *Efficacy* [92, 184, 221].

The collective identity is the part of an individual identity that is derived from (perceived) membership of a group [193]. Collective identity relates positively to both emotions and efficacy: Stronger association with a group results in stronger emotions from (perceived) injustices towards that group [92, 184, 221]. Additionally these emotions from perceived relative inequalities are a better predictor for participation in protests than objective group-based deprivation [92, 184, 221]. The efficacy is the perception of an individual that joining in collective action will be successful and have the desired effects [92, 184, 221]. More important is *group efficacy*, the belief that changes can be induced by acting as a group. Therefore a stronger collective identity is also positively related to efficacy.

These sociopsychological frameworks also describe a *frame*; how the issue or cause of a movement is presented by the organisers and in the media, and consequently how it is perceived by individuals [221]. Such frames are often built upon an existing collective identity [155]. Important for the spread of riots is that such a frame aligns with the grievances of individuals, such that they can identify with the goal and intentions of the movement. One suggestion for the widespread unrest in the Arab Spring is the existence of a pan-Arabic identity [64]. The frame of the protests movements then also applied to other countries due to the cultural and social similarities, and comparable grievances about authoritarian regimes.

Another explanation for the spread of violence in both the Arab spring and the England riots that same year is the role of (online) social media. Information about a (potential) protest or riot has to travel to individuals in other locations such that they can initiate their own gatherings. Information about such events is primarily shared through interpersonal contact [176]. Through the introduction of online social media like Twitter and Facebook, the density of the contact networks between individuals has significantly increased, decreasing distances between communities in such networks [107]. Additionally many of the online social media platforms include ways to share information simultaneously with multiple or even all contacts [15, 75],

## 5.1 Introduction

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further increasing the rate at which information flows through a network.

Both the similarity of interests or grievances between communities (segregation) and the properties of the contact network (fragmentation) are important for determining the spread of violence. If two locations are very sparsely connected, information about unrest in one location might spread very slowly or not at all to another location. Likewise if the frame of the riot does not apply to another location, the members of that community will not engage in the unrest, even if the network density or geographic proximity is very high. In the London riots for example not all boroughs suffered from the widespread looting during the London riots [121]. Despite geographic proximity to riot locations, there was little motivation for individuals in many boroughs to exploit the absence of police by engaging in opportunistic looting because there was less economic deprivation [163].

This leads to the question of how the overlap of a riot frame between contrasting hardship structures of different communities and their interconnectivity influence the probability that unrest will spread from one location to another. To answer this research question I use an agent-based model. Using such a model allows me to implement specific social network structures, and explicitly control key topological properties of the network (e.g. density). Additionally I can also assign different types of grievances at both the individual and group level, rather than assuming homogeneity at any particular level or organisation (mean-field).

Previous research in the the diffusion of riots and other forms of civil violence has focused on finding evidence of contagion and characterizing spatial patterns. Myers for example re-examined the events of racial disturbances in the 1960s, concluding that mass media facilitated the spread of violence across cities [131]. Additionally Myers finds that within this period the influence of contagion decays over time, but is mitigated by geographical proximity of cities [132]. The severity of the riot also influences the probability of transmission of disturbances from one location to another [132]. Similar statistical analyses have also been applied to the 2011 London riots, but focus on the (local) spread within one single city instead of regional diffusion [16, 17]. Since these studies rely on statistical analyses of these events, they can characterise spatial patterns and relationships, but cannot describe how the probability of contagion and coalition formation between communities is influenced by different levels of (interest/hardship) segregation and the properties of the contact network between individuals.

Previous numerical models of riots and civil uprisings have mainly expressed the motivation to join such events as a single dimensional number between 0 and 1, mostly uniformly distributed, often named hardship or grief [48, 55, 129, 198]. In this chapter I split the concept of hardship into multiple dimensions to describe grievances about different issues. Using this novel approach I can explicitly control the segregation of hardship between different groups, as well as correlate hardship in individuals along different dimensions. The model can then be used to study under which conditions individuals and groups with different primary grievances still opt to join the riot, forming coalitions and facilitating the spread to another location.

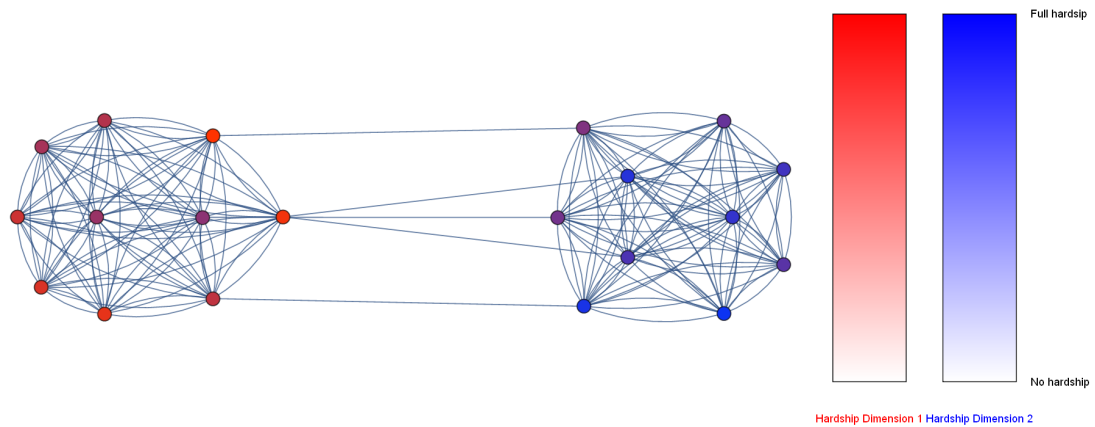


## 5.2 Model

I use an agent-based model to answer the research question of under which conditions riots spread from one location to another, and to investigate the effects of network density, riot frames, and hardship segregation. The model that I use in this chapter is a small variation on the model described in Chapter 3. As the investigations are not related to any specific real-world location, I omit the age amplification factors that influence the hardship of the agents. A summary of the model description without the motivation for the model design can be found in Appendix 8.7.

## 5.3 Methods

To study the spread of riots from one location to another I create two separate riot locations with a fixed agent population size (see Figure 5.1). I start the riot in one of the two clusters, and study under which conditions the riot spreads to the second cluster. During each iteration agents can join and leave the riot at their location, and the iterations represent 30 minutes. Every 24 hours after the (manual) initiation of the first riot, the agents can group together to start a new riot.

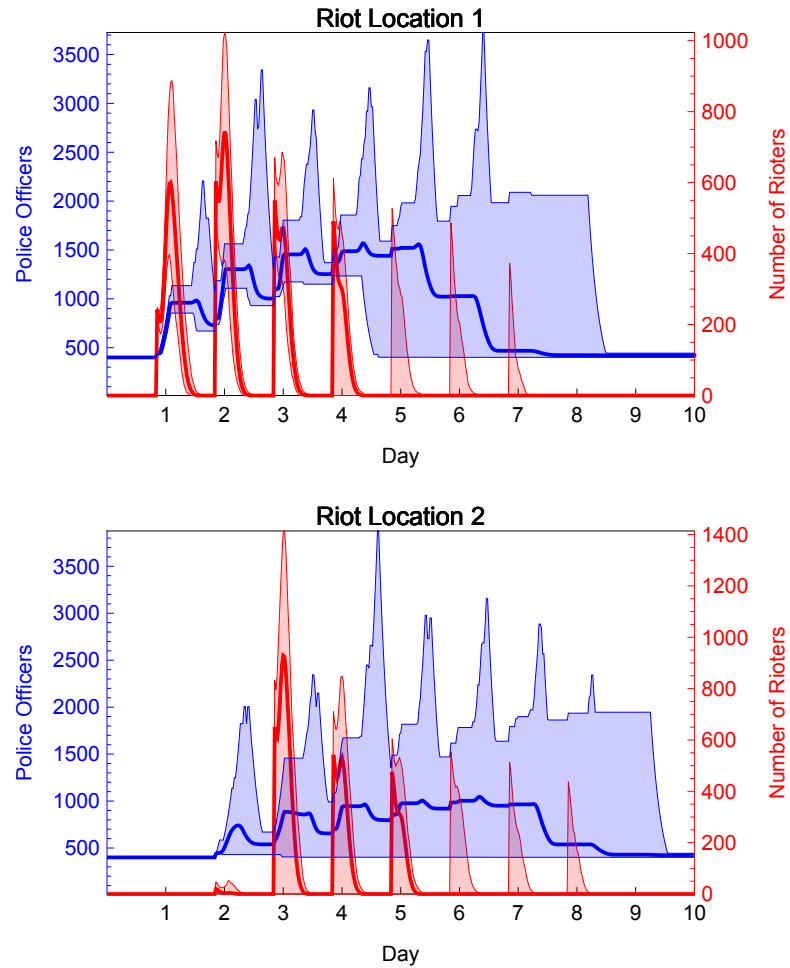


**Figure 5.1: Two interconnected agent contact network clusters.** *The clusters represent potential riot locations. Each community of agents in the riot locations is aggrieved for different reasons, represented by the colour of the nodes.*

To compare the effect of different parameter settings and initial conditions I describe a ‘standard run’ with parameter settings as shown in Table 5.1. Figure 5.2 shows the model behaviour for two separate riot locations with the parameter settings described in Table 5.1. The first riot starts in location one at 20:00 lasting the night, and spreads to the second location the next day. The duration of the riot in cluster 1 is between 3 and 7 days, with the median riot lasting 4 days. Location 2 starts with a very small riot on day 2 that spreads over from location 1. The riot in location 2 lasts between 1 and 7 days, with the median riot also lasting 4 days.

Symbol	Description	Units	Value
$N$	Number of Agents	Agents	10,000
	Number of Riot Locations	Locations	2
	Riot Location Cluster Size	Agents	5,000
$2k$	Number of Agent Connections		30
$p$	Rewire Probability		0.14
$q_{\text{out}}$	Rewire Probability Out		0.1
$N_{R0}$	Riot Start Size	Agents	250
	Riot Start Time	Hours	20
$\alpha$	Communication probability		0.5
$\omega$	Memory capacitance	$t^{-1}$	0.5
$\beta$	Network control 1		0.15
$\gamma$	Network control 2		2.5
$\delta$	Deterrence	Rioters/Police officers	1
$\varepsilon$	Fatigue		0.13
	Cooldown	Hours	12
$\theta$	Segregation Angle	Degrees	0
$F_\phi$	Riot Frame Angle	Degrees	45
$P_{\text{min}}$	Start Police per location	Officers	400
$P_{\text{max}}$	Maximum total Police	Officers	10000

**Table 5.1: Model parameter values for reference run.**



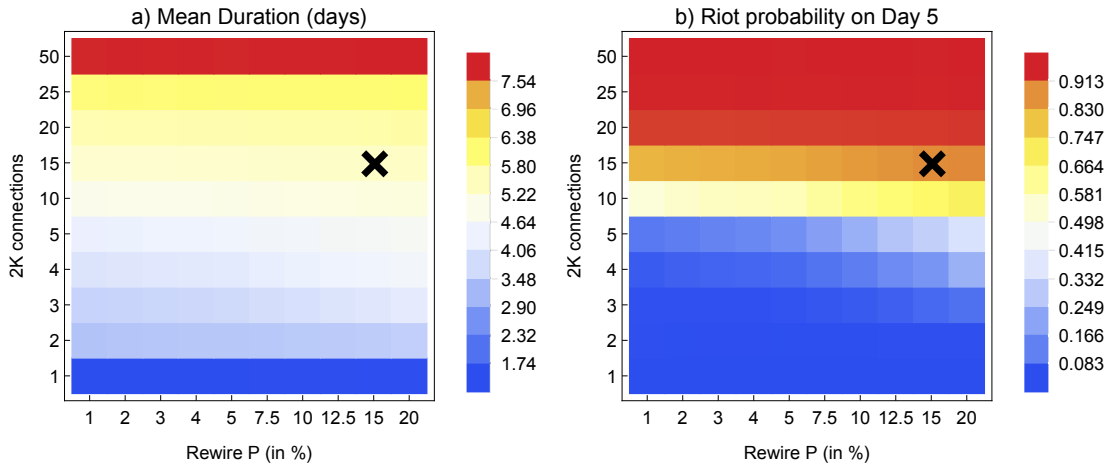
**Figure 5.2: Reference model run showing riot and police activity in two riot locations.** The number of rioters (red) and number of police officers (blue) in riot location 1 (top) spreads over to location 2 (bottom). The median number of rioters and police officers is shown in bold, and the variance is shown in the faded background.

## 5.4 Results

### 5.4.1 The Effect of Network Structure in a Single Riot Location

The agents in the model can only join the riot once they have been alerted that such an event is in progress. The dissemination of information in the model is dependent on communication between agents, which is enabled through their contact network. To study the effect of communication on riot behaviour I start by considering only a single riot location. The network structure is changed by varying the two parameters associated with the network: the number of connections per agent,  $2k$ , and the rewiring probability  $p$ . The number of connections changes the overall density of the network, and the rewiring probability affects the network structure, determining the degree to which the network is a random network.

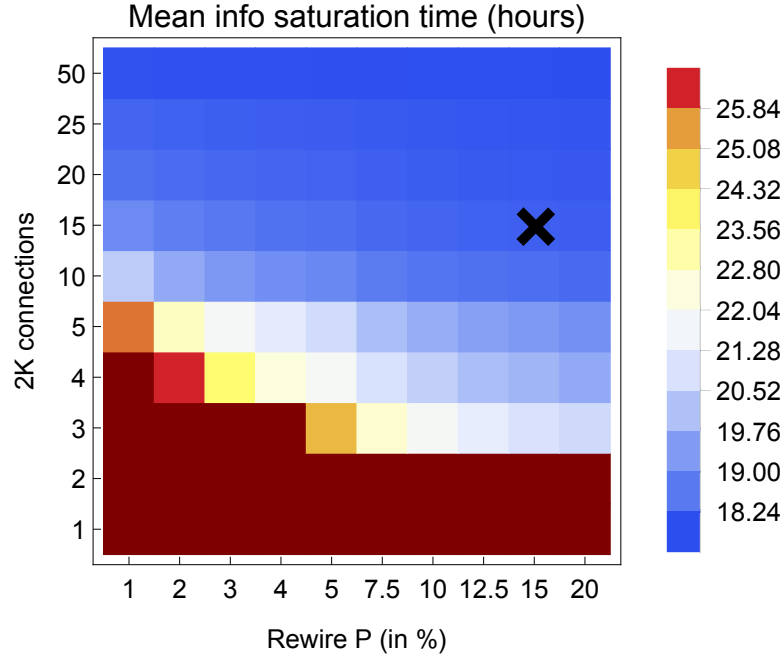
Figure 5.3 shows that both the duration and the probability of a 5-day riot increase with higher network density ( $2k$  connections). Altering the structure of the network (rewire probability) has almost no effect on the duration. Shifting the network topology towards a random network does affect the probability of a 5-day riot, but the impact of the network structure decreases as with higher density (Figure 5.3b).



**Figure 5.3: Effect of network properties on a single riot location.** *Effect of network structure (x-axis) and density (y-axis) on a) mean riot duration and b) the probability of a minimum 5 day riot. The cross denotes the 'standard' parameter settings from Table 5.1.*

The increased density of the network has a positive effect on duration and riot probability because the information about the riot travels faster through the network. Figure 5.4 shows the effect of the different network density and structure on the

average earliest time by which all agents know about the riot. The increased density lowers the time by which all agents are alerted about the unrest. The earlier agents are alerted, the earlier they can join, increasing the activity and the probability of a riot. Moreover the higher network density increases the chance that an agent knows another agent that is currently in the riot, increasing their own propensity to join.



**Figure 5.4: Mean earliest knowledge full saturation time under different network configurations.** *The agents share knowledge about the riot with each other through the contact network. I measure the earliest point at which, on average, all agents know about the existence of the riot. Not at all parameter settings are all agents alerted to the existence of the riot, shown by the bordeaux red surface. The cross denotes the reference model parameter settings from Table 5.1.*

#### 5.4.2 Interconnectivity between Riot Locations

Unrest spreads from one location to another through the flow of information, for example over an interpersonal communication network between individuals. In my model the riot starts in one location, and spreads to another through the interconnecting edges between the two agent clusters. To study the effect of the interconnectivity of the riot locations on the spread of violence I describe two riot locations, and vary the global rewiring probability  $p$ , describing the degree to which the network is a random network, and introduce a new variable  $q_{out}$ , describing the probability that a rewired edge in the small world network is wired to the other

## 5.4 Results

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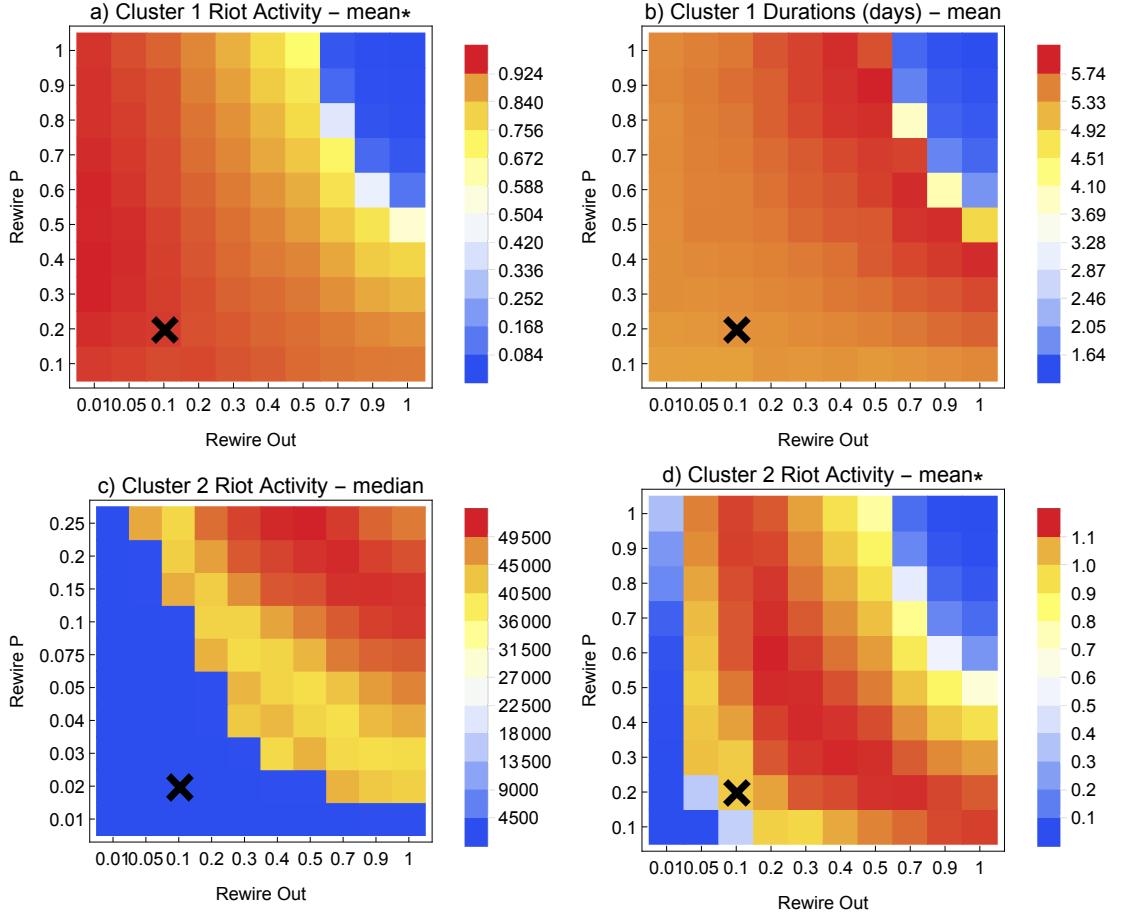
cluster instead of rewired within the originating cluster.  $p$  is then a measure of how many edges are expected to be rewired,  $q_{\text{out}}$  describes the mean fraction of those rewired edges that are rewired to the other riot location. The total number of edges in the network remains the same regardless of the values of  $p$  and  $q_{\text{out}}$ . I conduct an alternative experiment in Section 5.4.2.1 in which I keep the structure of the two riot locations intact, and add connections between the two locations instead.

Figure 5.5a shows that the mean riot activity in cluster 1 decreases as the number of connections wired to the other cluster increases. Because the number of edges remains constant, wiring more edges to the other riot location results in a lower internal density in cluster 1. The lower local density slows the dissemination of information in location 1, reducing overall riot activity because as a significant portion of the potential riot body is excluded from joining the riot for a prolonged time. Eventually the loss of internal connections is so extreme that the information no longer reaches enough agents to sustain riot activity, and as a result the activity and duration collapse (see Figure 5.6).

Increasing the number of edges between riot location 1 and 2 decreases the riot activity in location 1, but increases the duration before it falls sharply together with the riot activity (Figure 5.5b). The duration increases due to the lower speed of information spread. Despite the lower rate at which the information spreads all agents are still informed (Figure 5.6a), but because they are alerted to the riot at a later stage the resulting riot duration is longer.

Figure 5.5c shows that there is a sudden shift in riot activity in location 2 as the number of edges between the two clusters increase. Note that the range of the rewire probability is smaller than in the other panels, highlighting the sensitivity of riot spread to the interconnectivity between the locations. If there are not enough connections between the two clusters there is no riot activity, demonstrating that there is a clear minimum number of connections necessary to support the spread of the riots from one location to the other. I show the median instead of the mean to emphasize the strong contrast in riot behaviour at different levels of interconnectivity between the two riot locations.

The mean riot activity in cluster 2 initially increases with higher levels of interconnectivity, but like location 1 the activity lessens as more internal edges are traded off for externally rewired edges (Figure 5.5d). The diagonal pattern shows that there is an optimum number of connections to the second cluster in terms of the local



**Figure 5.5: Riot activity and duration in two riot locations with different degrees of interconnectivity.** The effect of number of rewired edges (y-axis) and fraction of rewired edges to the other cluster (x-axis) on a) the mean riot activity in location 1, b) the mean riot duration in location 1, c) the median riot activity in location 2, and d) the mean riot activity in location 2. The cross denotes the reference parameter settings from Table 5.1. The values in panels a) and d) are expressed relative to the standard run, denoted by the asterisk in the panel title.

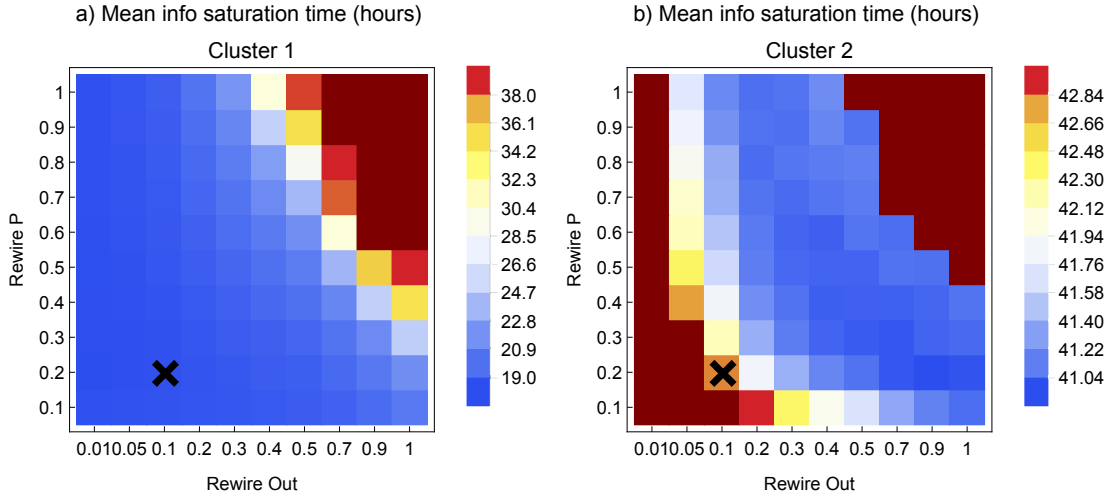
riot activity. This optimal interconnectivity coincides with the earliest point at which all agents on average know about the riot (Figure 5.6).

#### 5.4.2.1 Interconnectivity continued - adding instead of rewiring edges

By only changing the rewiring probability  $p$  and the fraction of rewired edges to the other cluster  $q_{\text{out}}$  the number of edges in the network remains the same regardless of parameter settings. However as Figure 5.5 shows, there is a trade-off in this experiment as the number of edges between the two riot locations increases. Interconnectivity between the clusters comes at the cost of local density, lowering the



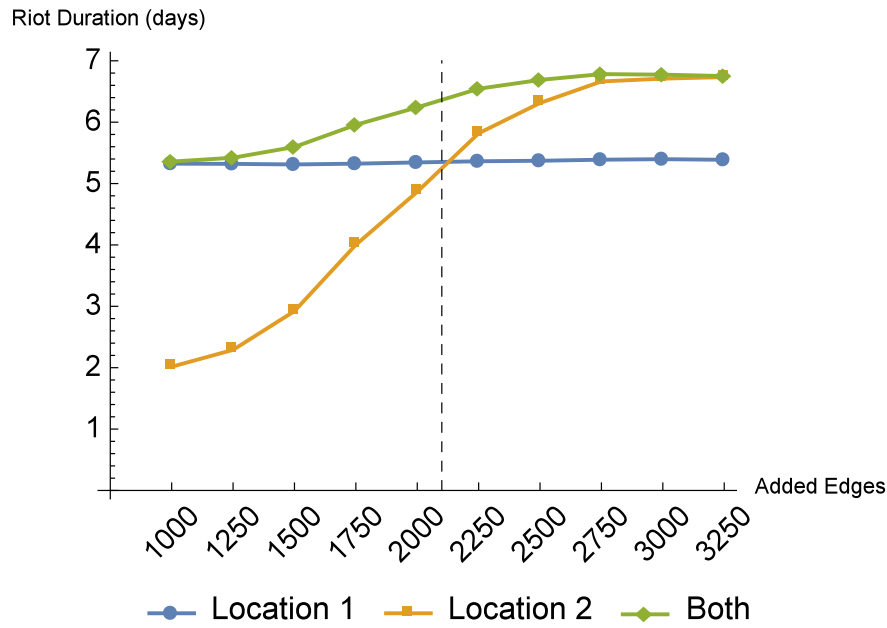
## 5.4 Results



**Figure 5.6: Mean earliest knowledge full saturation time under different network configurations in two riot locations.** *The agents share knowledge about the riot to each other through the contact network. I measure the earliest point at which, on average, all agents know about the existence of the riot. a) shows the earliest point at which all agents in riot location 1 know about the riot, b) shows the same for riot location 2. Not at all parameter settings are all agents alerted to the existence of the riot, shown by the bordeaux red surfaces. The cross denotes the reference model parameter settings from Table 5.1.*

riot activity severely if too many internally wired edges are taken away. Therefore I set up an alternative experiment, where I keep the internal structure of the locations the same, and increase the interconnectivity by adding random edges between the clusters.

Figure 5.7 shows that the riot duration in cluster 1 is not influenced by the number of connections added to the other riot location. The riot duration in location 2 increases from 2 to 7 days as more edges between the locations are added, in the shape of a sigmoid or logistic function. The largest increase is between 1750 and 2250 added edges, where the additional 500 connections between the total of 10.000 agents changes the average riot duration from 4 to 6 days. This increase coincides with the threshold shown in Figure 5.5c, where around 1800 edges the riots spread to the second cluster.



**Figure 5.7: Riot duration and network cluster interconnectivity.** *The influence of added edges between riot locations on riot duration in location 1 in blue, location 2 in orange, and both locations in green. The dashed vertical line denotes the interconnectivity in the 'standard' model run from Table 5.1.*

### 5.4.3 Introducing Hardship Segregation between Two Communities: Small Levels of Segregation Increase Riot Activity

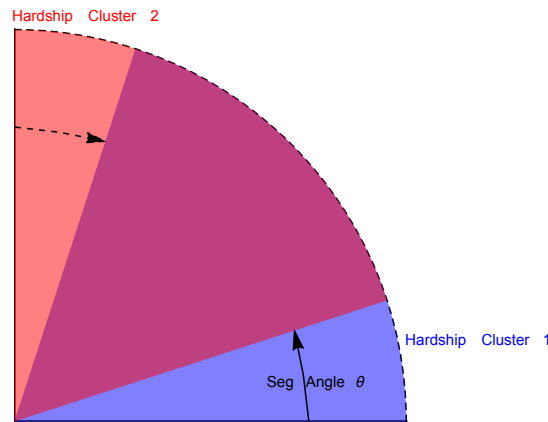
Another important factor in facilitating riot spread besides the contact network is the overlap in hardship between communities. The interconnectivity between riot locations allows the information about unrest to travel, but in order for another community to start unrest in their location, their grievances have to resonate with the riot frame. I split the hardship  $H$  of agents into multiple dimensions to describe grievances about different issues, and describe the riot frame  $F$  along those same dimensions. The affinity of an agent with the riot, i.e. the internal motivation, is then obtained as the overlap between an individual agents hardship and the goal of the riot, defined in equation 3.4.

Using two riot locations and two hardship dimensions, I describe the difference in grievances between the two communities by a segregation angle  $\theta$ . I segregate the agents according to hardships in these riot clusters to study under which conditions they form coalitions and join the riots. For example, one of the two communities

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might be heavily aggrieved about the lack of (good) schools in their area, while the main issue in another area relates to ethnic profiling. In this experiment the segregation angle  $\theta$  describes the degree to which each community is aggrieved by their own local independent issues. Both communities might have the same problems, representing low segregation of hardship, or only be aggrieved about issues local to their area, which corresponds to the situation of high hardship segregation. I vary the segregation angle together with the riot frame, which represents the main issue of the riot, to find out under which conditions the second riot location is conducive to coalition forming with the first cluster, and facilitates the spread of the riots from the first to the second location.

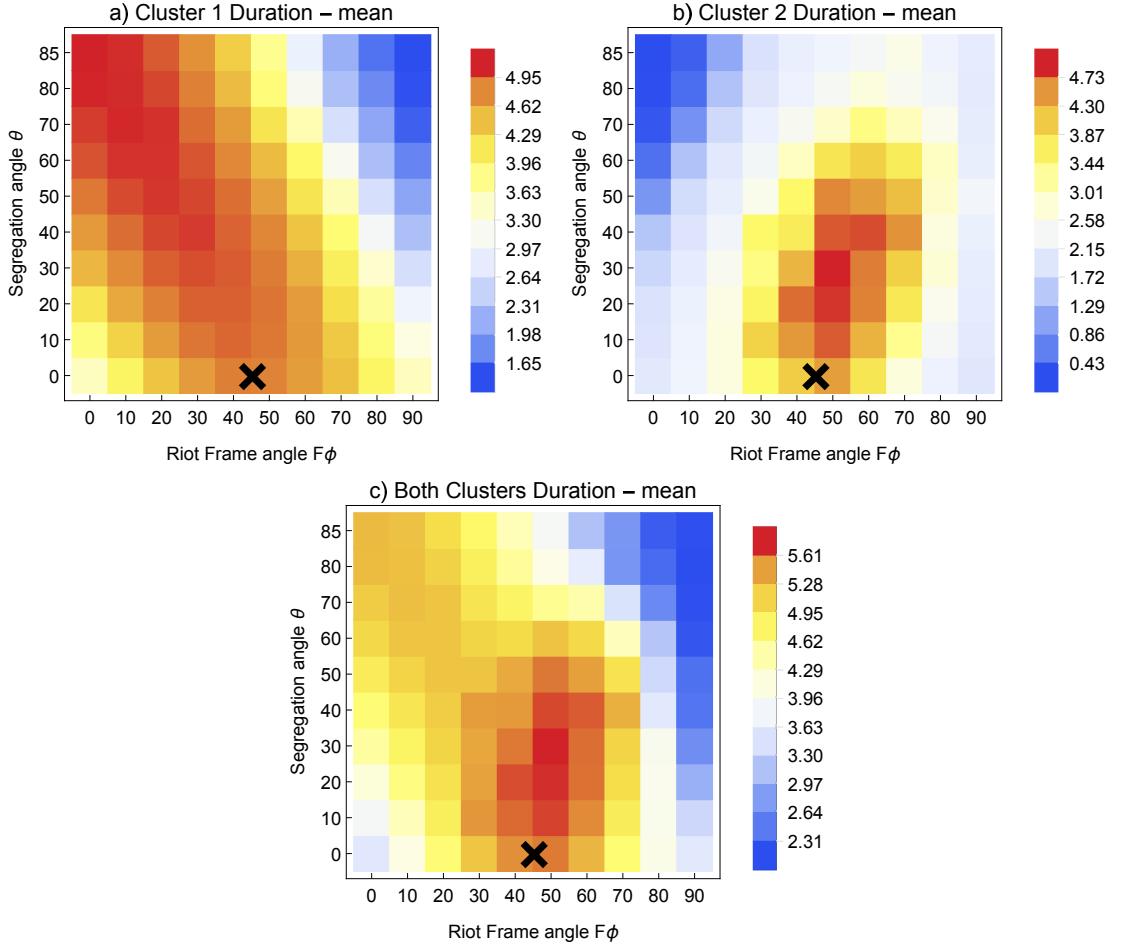
The hardship  $H$  of an agent is described in polar coordinates, such that it can be generated using a radius and an angle between 0 and 90 degrees. I introduce a segregation angle  $\theta$ , measured in degrees, that changes the angular range from 0 to  $90 - \theta$  degrees in location 1 and from  $\theta$  to 90 degrees in location 2 as shown in Figure 5.8. The segregation of hardship in each riot location makes the agents in each cluster more prone to care only about one of the two grief issues. I also vary the riot frame  $F$ , described by the angle from the x-axis in degrees (see Figure 3.2).



**Figure 5.8: Segregation angle  $\theta$  in two communities and two dimensions.** *The segregation angle limits the angular range of the hardships in each community. In location 1 numerical range of agent hardship is between 0 and  $90 - \theta$  degrees, and conversely in location 2 between  $\theta$  and 90 degrees. The axes represent the two issues about which the agents can be aggrieved.*

Figure 5.9a shows that increasing segregation combined with a riot trigger that is mainly about issue 1 ( $F_\phi$ , the angle of the riot frame in regard to the x-axis, is small) increases riot duration in location 1. By increasing the segregation of hardship,

the variance in hardship in the communities becomes lower as the angular range or variation of the hardship narrows (see Figure 5.8). At the same time the mean local hardship in that community shifts from 45 to 0 degrees as the segregation angle  $\theta$  increases. The riot activity is highest when the riot frame is aligned with the mean hardship of that community, as shown by the diagonal increase in Figure 5.9a when simultaneously increasing the segregation angle  $\theta$  and decreasing the riot frame angle  $F\phi$ .



**Figure 5.9: Interactivity between hardship segregation and riot frame on riot duration.** Effect of segregation (y-axis) and the riot frame (y-axis) on mean riot duration measured in days in a) location 1, b) location 2, and c) both riot locations. The cross denotes the 'standard' parameter settings from Table 5.1.

Likewise the riot duration in location 2 also becomes longer when segregation increases and the riot trigger is more about issue 2 than issue 1 (Figure 5.9b). If the angle of the riot frame becomes too large (too much about issue 2), the riots in location 1 decrease because the resonance between  $F$  and the hardship in that community

## 5.4 Results

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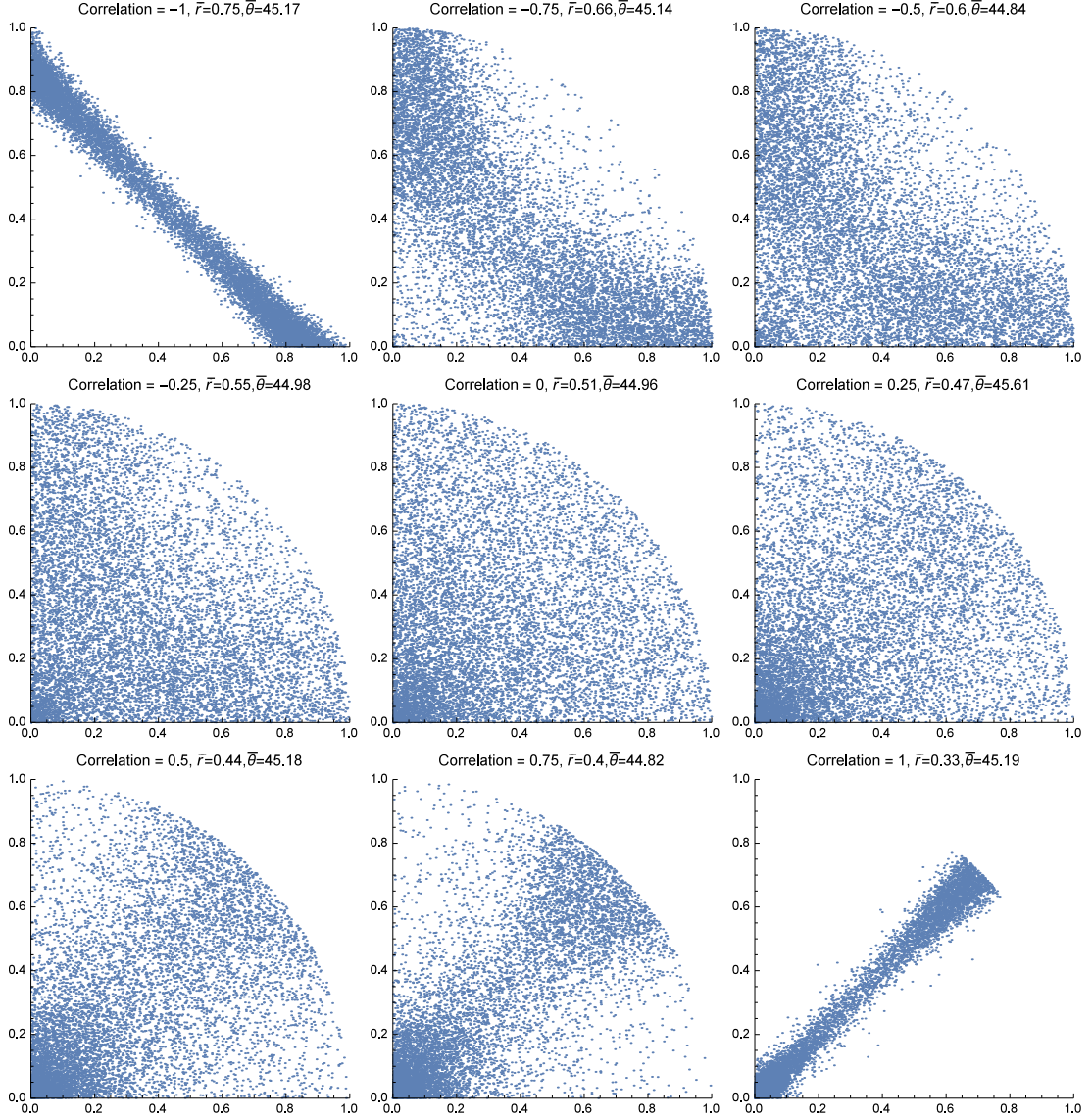
becomes weaker. Lower riot activity in cluster 1 results in a weaker spread of violence to location 2.

If the riot is equally about both issues (45 degrees), increasing the segregation initially increases riot activity and duration in both riot locations (Figure 5.9c). The increasing segregation decreases the local variation in hardship, strengthening the collective identity of the agents in each cluster, resulting in more riot activity. Further increases in segregation reverse this effect, where the mean hardships in each community are too far removed from the riot frame and consequently the total riot duration and activity in both riot location decreases.

### 5.4.4 Correlating Hardship Dimensions

Up until now I have considered the two hardship dimensions as two independent issues. Sometimes two issues can be related, for example an area that mainly consists of two ethnic minority groups, that both experience different degrees of segregation and social exclusion. To implement such a relation in the model I correlate the two hardship dimensions, describing the degree to which these issues are positively or negatively related. The correlation is imposed using an approach that involves iterative random shifts of the individual hardships of the agents, accepting changes if the shift improves the correlation towards the correlation target and rejecting otherwise. I reject samples that create a different mean radius and angle compared to uncorrelated hardship distributions. An example of the hardship distribution after imposing a correlation is shown in Figure 5.10, together with the effect on the mean radius when not rejecting samples properly (Figure 5.12 shows an example with sample filtering, leading to a stable mean hardship radius under all correlation levels).

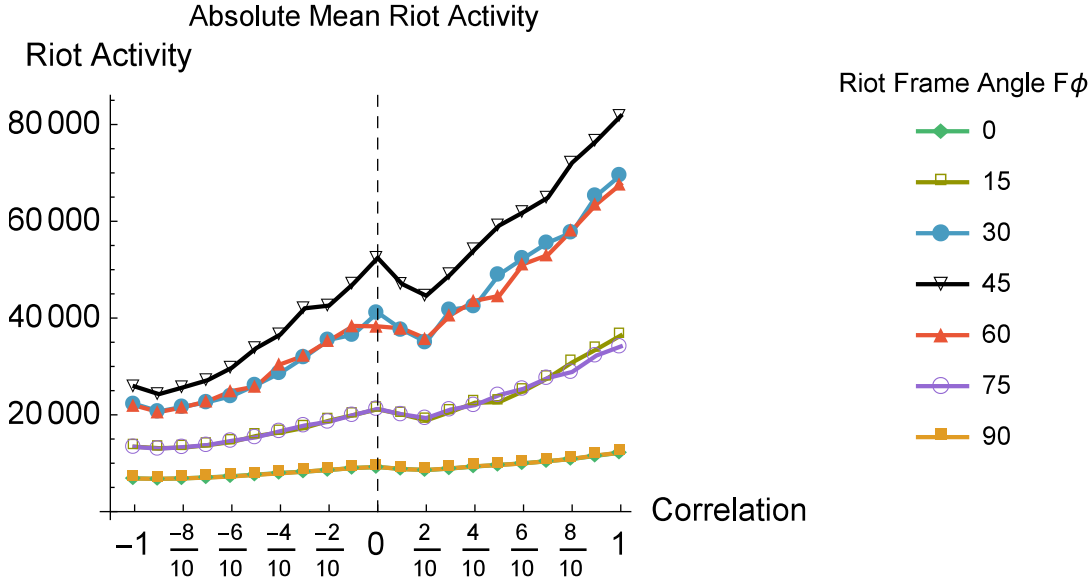
Figure 5.11 shows that large negative correlations between hardship in the two agents decrease riot activity when the riot is equally about both issues (riot frame angle at 45 degrees), while large positive correlations increase riot activity. Small correlations have the opposite effect; small positive correlations decrease activity compared to no correlation, and small negative correlations increase riot activity. This effect is further discussed in Section 5.5.1. Riot frames that deviate from the mean hardship result in a decrease in riot activity, weakening the effect of correlation.



**Figure 5.10:** Examples of imposing a correlation between the two hardship dimensions, and the effect of naive implementation on mean hardship radius and angle. The hardship distribution of the agents is shown for different levels of correlation, along with the mean hardship radius and angle of the distribution in the title in each pane. The mean radius decreases as stronger correlations are imposed between the hardship dimensions. Figure 5.12 shows that a different approach leads to a stable result.

#### 5.4.5 Riot Frames, Segregation, and Correlation

The relationships in the hardship dimensions can also be imposed through correlation in combination with segregation of hardship between communities. An example of combining segregation of grievances and correlation is shown in Figure 5.12. With the segregation angle  $\theta$  set at 45 degrees, such that there is no overlap between hardship



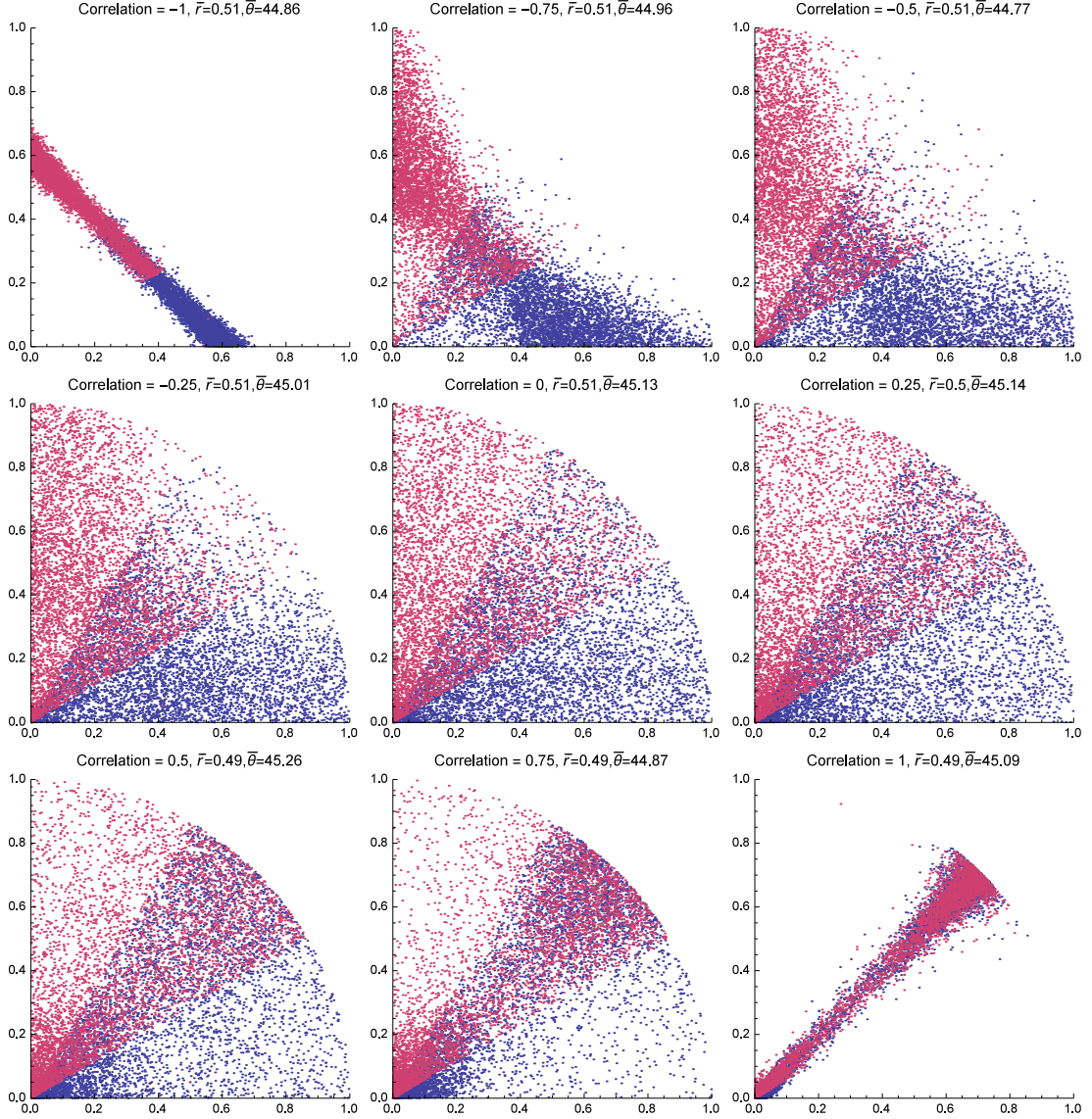
**Figure 5.11: Absolute riot activity at different levels of correlation of hardship dimensions and riot frame angles in both riot locations.** The absolute level of riot activity in both is shown on the y-axis, measured as the cumulative number of iterations that all agents engaged in the riot. The x-axis shows the different correlation levels. The different colours represent different riot frame angles, measured in degrees from the x-axis (see Figure 3.2). The dashed vertical line denotes the correlation in the reference run.

in the two communities, Figure 5.13a shows that in location 1 the riot activity increases with negative correlations at low riot frame angles (riot is more about issue 1). This contrasts with the previous result, where negative correlations dampened riot activity without segregation (Figure 5.11).

The riot frame angle changes the dynamics in riot location 1 considerably (Figure 5.13a). When the riot is equally about both issues ( $F_\phi$  is 45 degrees) or is more about issue 2, the riot activity uniformly increases with more positive correlations. If the riots are more about issue one ( $F_\phi < 45$  degrees), the riot activity initially increases as the correlation are less negative, but then decreases as the correlation becomes positive. The apex of this convex shape shifts to lower correlation values as the riot frame angle decreases. Eventually the apex shifts so low that the riot activity uniformly decreases with less negative and more positive correlations.

The effect on the riot duration in location 1, as shown in Figure 5.13b, is less drastic compared to the riot activity. Whereas the riot activity increases by more than 50% compared to no correlation and a riot frame at 45 degrees (Figure 5.13a), the duration increases at most by a single day. Similarly comparing the reference run to





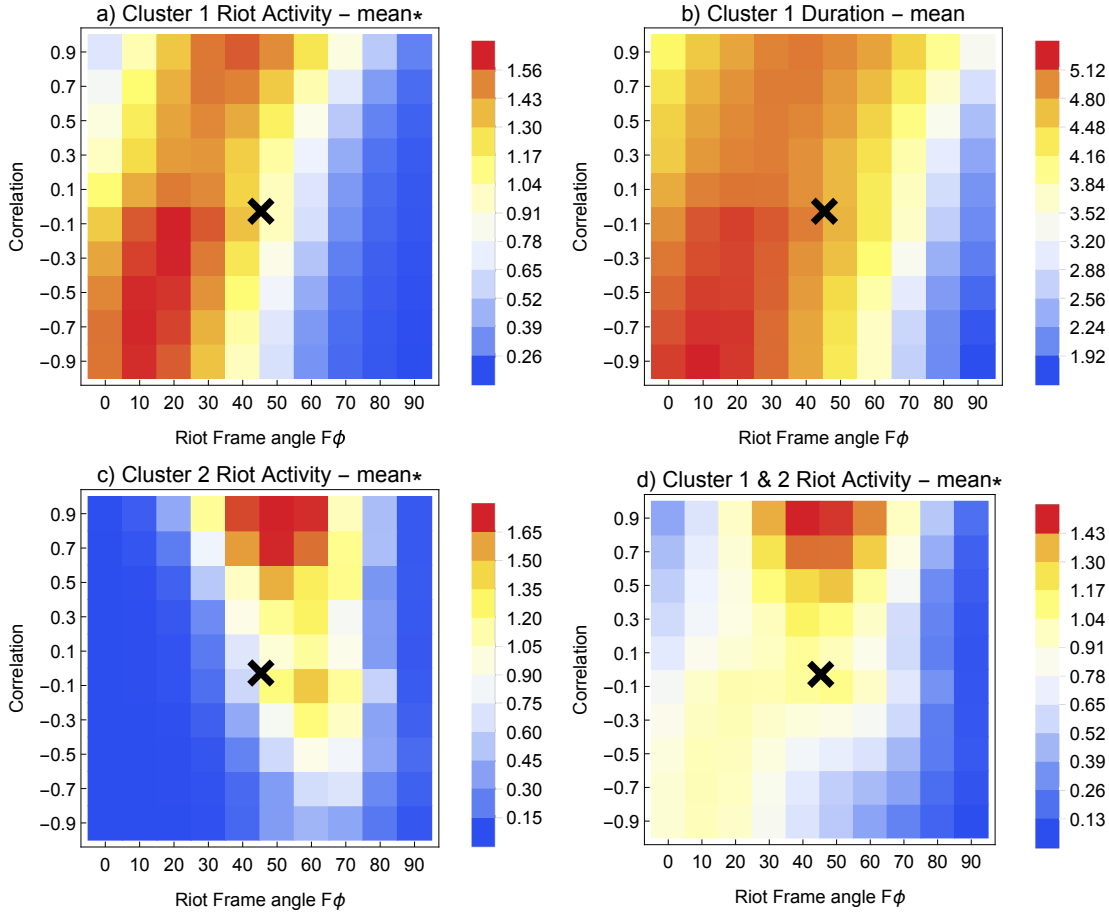
**Figure 5.12: Examples of imposing a correlation between the two hardship dimensions in combination with a segregation angle of 30 degrees.** *The hardship distribution of the agents is shown for different levels of correlation, along with the mean radius and angle of the distribution. The hardship of riot location 1 is shown in blue, and of location 2 in red.*

parameter settings of low correlations combined with a riot frame angle of 70 degrees, the duration drops from 4 to 3 days, whereas the riot activity drops by 50%. This highlights the wide range of riot behaviours of the model within relatively similar duration times.

The riots in cluster 2 generally increase with positive correlations when the



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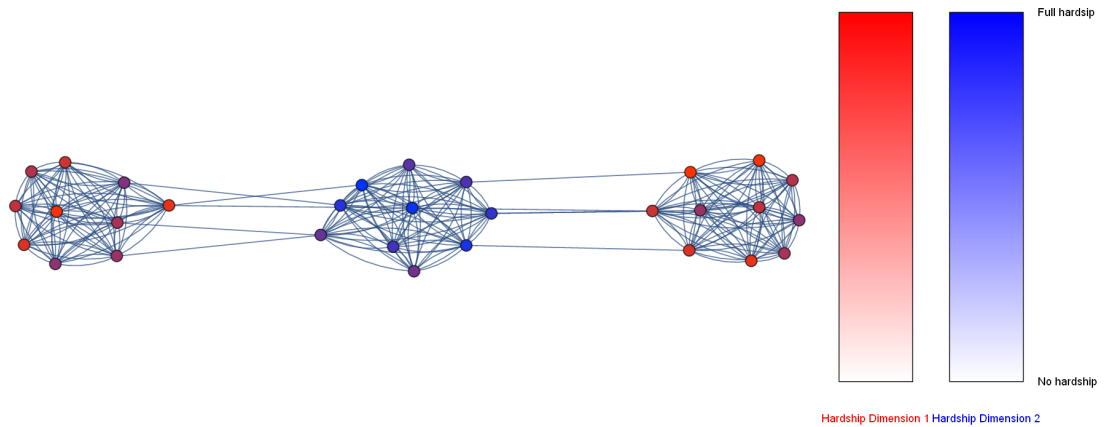


**Figure 5.13: Effect of correlation and 45 degrees of segregation.** *The effect of riot frame angle (x-axis) and correlation of hardship in two dimensions (y-axis) on a) mean riot activity in location 1, b) mean riot duration in location 1, c) mean riot activity in location 2, and d) mean riot activity in both locations. The values of panels a), c), and d) are expressed relative to the standard parameter settings, denoted by the black cross.*

hardship dimensions are fully segregated (Figure 5.13c). Like in figure 5.11 there is a slight increase at small negative correlations caused by the underlying algorithm that creates the correlations (see Section 5.5.1). Figure 5.13d shows the relative riot activity in both locations is highest at positive correlations due to the contribution from riot location 2. At low correlations and small riot frame angles the increased riot activity in location 1 compensates for the absence of unrest in location 2.

### 5.4.6 Three Riot Locations; Can a Riot Spread Silently to a Third Location?

The complex patterns of diffusion in the 2011 Arab spring can be distilled into two primary simplified patterns of spread [35]: 1) location A infecting a neighbouring location B, as shown in Figure 5.1, and 2) violence spreading from location A to a third location C, through a second location B, where B then does not experience any unrest (see Figure 5.14).



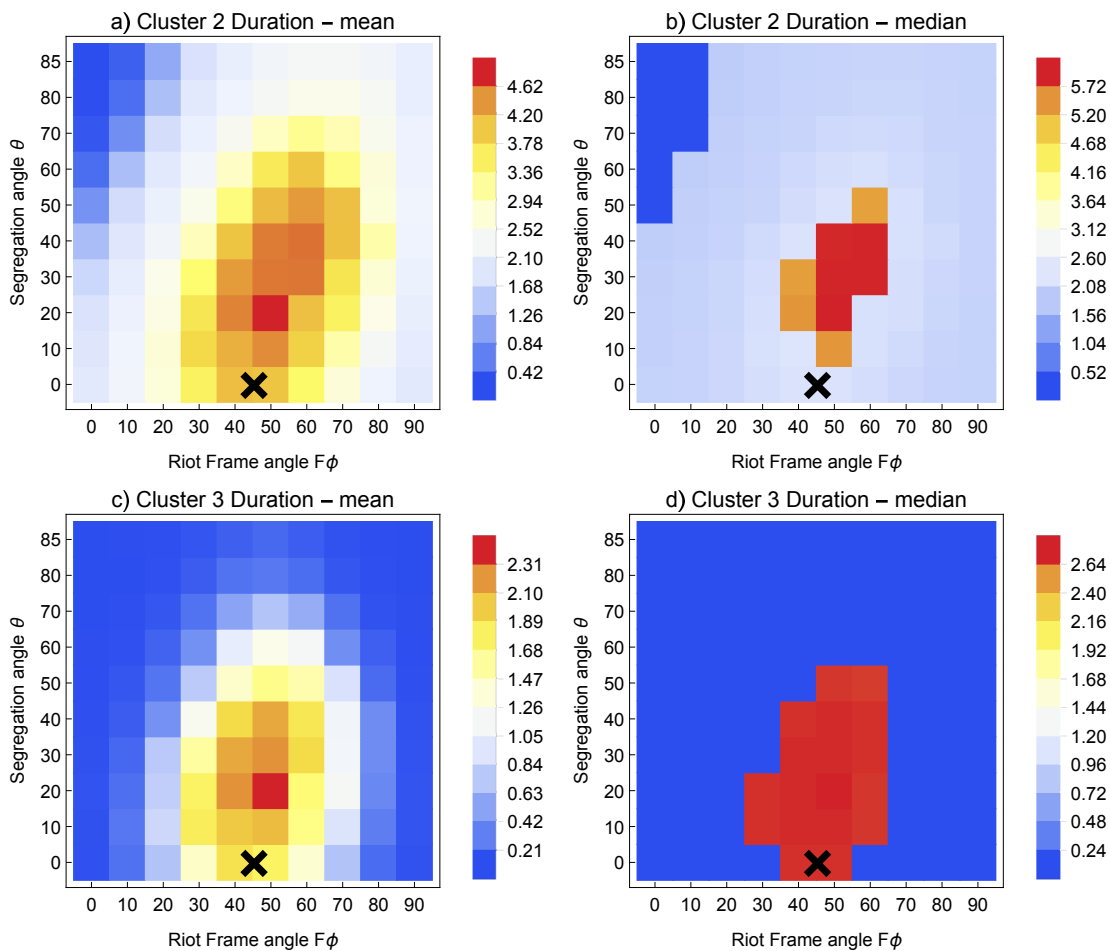
**Figure 5.14: Communication network structure for three riot locations.** *Experiment network and hardship structure setup for three riot locations. The riot starts in the left cluster, passes through the middle cluster without significant riot activity, and spreads further to the third riot location on the right. The outer network clusters are not connected directly to each other, forcing the spread through the middle cluster. The agents in the outer riot locations are aggrieved about the same issues, as opposed to those in the middle cluster, represented by the colours of the nodes.*

To investigate both patterns of spread I add a third riot location to the model, that is only connected to the second riot location. Riots can then only spread from the first to the third riot location by passing through the second cluster. For simplicity the agents in the third cluster have the same hardship structure as the population in the first riot location. The segregation angle  $\theta$  thus affects locations 1 and 3 in the same way, and location 2 adversely (see Figure 5.8). The main question of this subsection is when cluster 2 (location B) acts as an intermediary between the two outer riot locations (A and C), without experiencing significant unrest.

Changing the segregation in hardship between the communities and the riot frame angle, Figures 5.15c and d show that generally riots in location 3 only occur when there is a lot of activity in location 2 (Figures 5.15a and b). Despite the hardship

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in riot location 3 being the same as in riot location 1, the behavioural pattern of riot location 3 is the same as riot location 2 rather than 1 (see Figure 5.9). The spread of behaviour in riot location 3 is much smaller than in cluster 2, and generally riots in location 3 only happen if the riots in cluster 2 are more severe. The median behaviour shown in Figure 5.15b and d highlight this behaviour, showing the wider spread in behaviour in cluster 2 and the almost binary behaviour in cluster 3. It is therefore not possible for the violence to travel to the third location without activity in the second cluster under these model and parameter settings.



**Figure 5.15: Effect of riot frame angle and segregation on riot spread to secondary and tertiary locations.** Influence of riot frame angle (x-axis) and segregation angle (y-axis) on a) the mean and b) median riot duration in location 2, and c) mean and d) median riot duration in location 3. The black cross denotes the reference parameter settings.

Aside from the structure of hardship, the interconnectivity between riot locations is another important factor that determines riot spread, emphasised by the results shown in Figure 5.5. To investigate the effect of the network interconnectivity I vary

the probability that an edge is rewired to another cluster  $P_o$ . Because cluster 2 now connects to two clusters instead of one, I increase the standard parameter value of  $P_o$  from 0.1 to 0.15 to compensate for the edges that would normally go from riot location 2 to 1, but now go from 2 to 3.

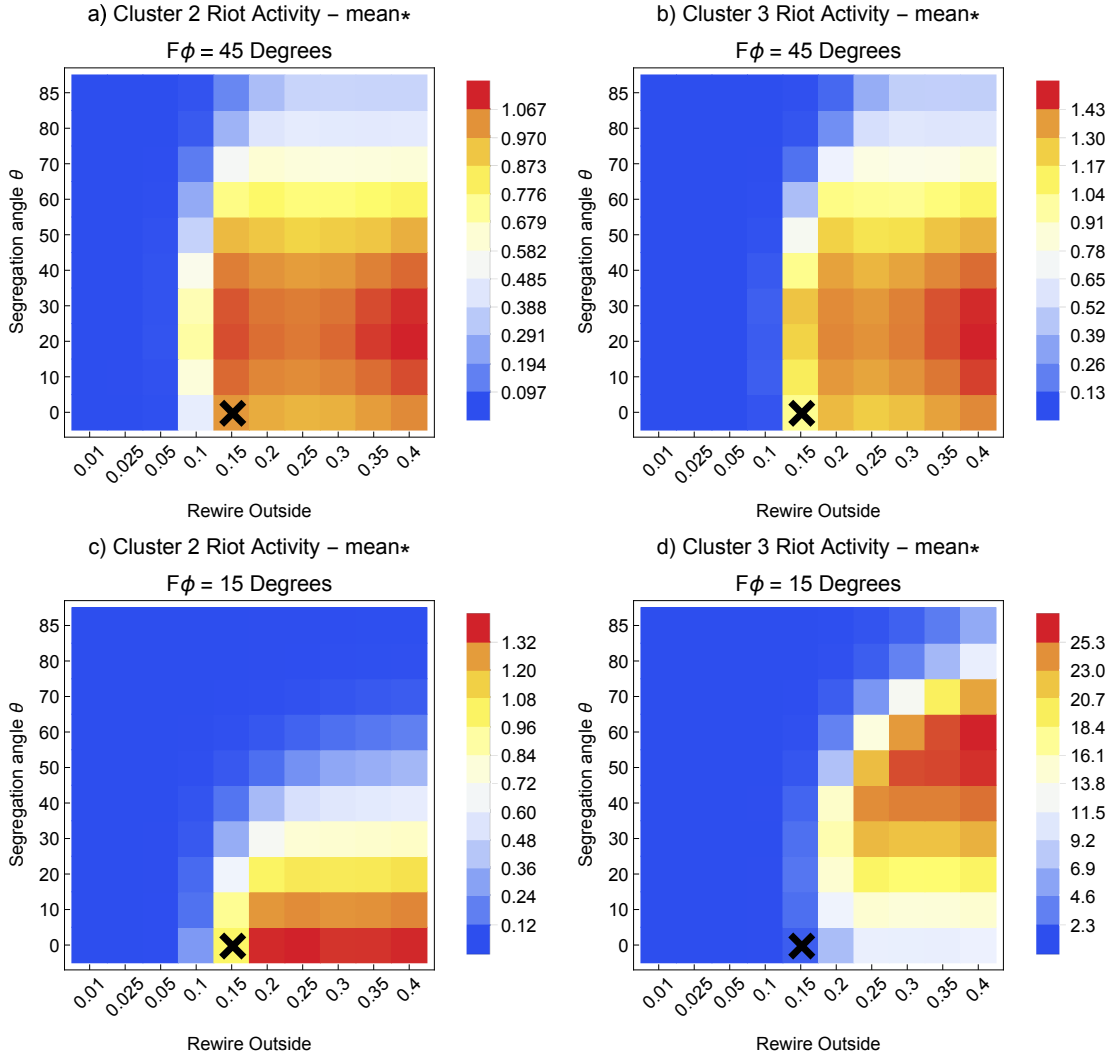
Figure 5.16 shows the effects of segregation and interconnectivity on riot behaviour at two different riot goals ( $F_\phi$  at 45 and 15 degrees) in riot locations 2 and 3. If the riot is equally about both issues (Figures 5.16a and b), then the behaviour in cluster 3 is similar to that of cluster 2, just like in Figure 5.15. However, when the riot frame angle is at 15 degrees (Figures 5.16c and d), making the riot more about issue 1 than issue 2, riots can occur in location 3 without relying on heavy riot activity in the second cluster.

Figures 5.16a and b) show the relative riot activity for riot location 2 and 3 at a riot goal of 45 degrees. The results for the added third cluster are the same for the two cluster setting (Figures 5.5 and 5.9), as the interconnectivity and segregation have similar effects. The mean relative riot activity generally increases with higher levels of interconnectivity, and small levels of segregation also lead to higher riot activity. Too large segregation between the groups result in a less intense riot. The riot behaviour in location 3 is similar to the riot activity in location 2, just like in Figure 5.15.

A riot frame angle  $F_\phi$  of 15 degrees, making the riot more about issue 1 than issue 2, results in different behavioural patterns (Figure 5.16c and d). At these parameter settings riots can spread to location 3 without depending on significant riot activity in location 2. The riot activity in both clusters increases with higher interconnectivity between the locations. Due to the increased number of connections between the clusters the riots can spread more easily. More agents in cluster 1 can spread the knowledge of the riot to agents in location 2, which in turn have a higher probability of also being connected to agents in location 3. The extra edges between the clusters allow the riots to spread at a riot frame angle of 15 degrees (Figures 5.16c and d), which does not occur with lower levels of interconnectivity (Figures 5.15c and d).

Increasing the segregation angle uniformly decreases the riot activity in cluster 2, but causes more riot activity in cluster 3. Because of the alternate riot frame angle of 15 degrees, increasing segregation decreases the overlap in hardship in the second location and consequently leads to less riot activity. Conversely the overlap in cluster 3 increases, leading to a higher riot activity. A segregation angle higher than 60 degrees also leads to less riot activity in the third location. The riot activity in the

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**Figure 5.16: Mean riot activity in cluster 2 and 3 at different levels of segregation and interconnectivity.** Mean riot activity with a riot frame angle at 45 degrees in a) cluster 2 and b) cluster 3, and a riot frame angle at 15 degrees in c) cluster 2 and d) cluster 3. The mean riot activity is expressed relative to the reference model run, denoted by the black cross.

third location peaks at the highest interconnectivity, and a segregation angle ( $\theta$ ) of 60 degrees. At those same parameter settings the riot activity in the second location are relatively low, resembling a situation where the riot spreads to location 3 through cluster 2, but without depending on heavy riot activity in the second location. At those settings the riot frame does not relate very well to the issues about which the agents in the second location are aggrieved, leading to very low levels of riot activity. The higher interconnectivity still allows the unrest to spread to the third location, creating the second pattern of spread where the second location only acts as a passive intermediary.

## 5.5 Discussion

In this chapter I have studied the progression of a riot in space from one location to another. I demonstrated how different variables like the (perceived) riot frame that results from a trigger event, correlation between grievances relating to two different issues, segregation of hardship between communities, and the network structure or fragmentation of three locations influences the probability of spread of a violence from one location to another.

Previous numerical models using agent-based methods have either considered space as a grid lattice (e.g. [55, 129, 198]), where agents can (randomly) freely move around, or have modelled different riot locations independently of each other (e.g. [48] and Chapter 4). Statistical methods have primarily focused on the frequency of unrest on the country level [31, 100], and have studied the diffusion of violence between and within cities [16, 17, 131, 132]. In this chapter I have followed the example of Brummitt by coupling multiple riot locations [35], but use an agent-based model to demonstrate how the influence of segregation and network properties influences the probability of spread.

The first result of this chapter is that the density of a communication network is more important than the network topology or structure for determining riot activity (Figure 5.3). Online social media like Facebook and Twitter have greatly increased the density of information networks [107], and therefore also boosted the speed by which information can be disseminated between individuals. The spread of riots mainly relies on information sharing through interpersonal contact, rather than TV or other media [176]. The introduced ‘hyperconnectivity’ between individuals makes riots longer and more intense according to the model. Myers concluded from his analysis on the spread of racial civil violence in the 1960s that cities have differential intrinsic propensities to riots, and thus also have distinct levels of resistance and responsiveness to such events [131]. One implication of this result is that such resiliencies, if they are due to particular network configuration in communities, might be weakened through the introduction of online social media and the accompanying rise in network density.

The density of the contact network between agents also influences the probability of the spread of violence from one location to another. Figure 5.5 shows that increased interconnectivity between communities promotes the contagion of riots. However,

## 5.5 Discussion

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the spread of riot activity as a result of the shared edges between the communities is characterized by a sudden shift or critical transition, rather than a gradual progression. The adoption of social media could therefore be one of the reasons why there was such a surprise about the spread of violence in the 2011 Arab spring and the England riots. The introduction of online social media has increased the density of interpersonal networks [107, 183], and therefore possibly also has established or reinforced links between different communities. Locations which were previously resilient to the spread of violence could have become susceptible to spread from unrest in other locations as they have become more interconnected. Additionally increasing the ties between communities can increase intergroup differences and polarisation [60], increasing conflict within those groups [56].

Network density and interconnectivity between different riot locations are not uniquely positively related to the spread of violence; counterintuitively in Thailand for example, the frequent escalation of conflict has been linked to the large distances in the network between different insurgent groups [123]. Although these groups have similar interest in rebellion, the network distance between them prevents them from cooperating and forming a coalition, thus leading to a situation where each group acts alone, resulting in the relatively frequent outbursts of conflict [123].

Figure 5.5 also shows that sharing too many connections with other riot locations decreases riot activity. This occurs because the edges shared with another cluster come at the cost of internal density, as the total number of edges in the network remains the same. These parameter settings represent a situation that is unlikely to represent the real world, especially when only considering two communities. At these settings agents then have a higher probability to interact with agents from the other community, than neighbouring agents in their own location. While this could be the case for some agents that for example recently moved, it would be an extreme case if this is true for all agents within the two communities. This only holds when considering only two locations, as with multiple locations the external connections are shared between several locations. It is then through these connections that unrest can spread, while still allowing agents to be relatively well-connected locally.

Introducing different hardship dimensions, the result shown in Figure 5.9 is that small levels of segregation in hardship between the two communities increases riot activity in both riot locations. The hardship dimensions relate to different issues, and segregating the hardships between the two clusters represents a situation in which two communities are aggrieved about different issues. In the model the

segregation angle  $\theta$  narrows the range of agent hardships in each location (see Figure 5.8), effectively strengthening their collective identity as a community. The stronger collective identities makes the agents more likely to join a riot when the riot frame aligns with that collective identity, as shown by the diagonal patterns in Figure 5.9. The peak riot activity occurs at 30 degrees of segregation. At a segregation angle  $\theta$  of 30 degrees the total hardship space is divided into 3 equal parts, with 30 degrees unique to each cluster and 30 degrees of overlap between the clusters.

### 5.5.1 Hardship and Correlation

In some cases two issues that cause grief are related to each other. Such a relationship is established in the model by correlating the hardship in agents along the different hardship dimensions. A positive correlation implies that if an agent is aggrieved about one of the two issues, that agent is likely to be equally aggrieved about the other issue. Conversely negative correlations imply that the more agents care about one of the two issues, the less likely they are to simultaneously care equally about the other. Figure 5.11 shows that generally, negative correlations between the two issues result in less riot activity, and positive correlations promote riot activity.

The relationship between the two hardship issues is introduced through a correlation along the two hardship dimensions. The correlation is achieved by randomly shifting the agent hardships within the available hardship space, dictated by the segregation angle. Shifts are accepted when the overall correlation improves towards the desired correlation target, and rejected otherwise. Additionally I also reject shifts that change the mean radius and hardship angle significantly.

Figure 5.11 shows that strong positive correlations increase riot activity, and strong negative correlations between the two issues dampen the riot activity. Both weak positive and negative correlations create an inverse patterns. Small negative correlations result in increase riot activity compared to no correlations, and small positive correlations result in less riot activity.

The inverse pattern at weaker correlations is created by the simple sieving method that I use to generate the correlation between the hardship dimensions, and is not a result of the model or agent behaviour. Despite that this is one of the most straightforward and simplest methods to create correlated distributions, it creates a problem with weak correlations that cannot be solved. Other methods that are



more complex might be better suited to impose correlations, but likely will show the same main result at strong correlations. However, another problem in generating correlated variables is that there are many possible configurations which result in the same correlation coefficient, but could result in different riot behaviour. A more complex method that solves the problem with the weaker correlations is therefore not necessarily better as there might be an inherent bias towards certain kinds of variable distributions.

One other method that is worth mentioning is the use of the Cholesky decomposition (for explanation see [26]), due to its efficiency and simplicity. I originally tried to use this method to generate correlated variables, but it turned out to be unsuitable for two reasons. The first is the method relies on the addition of  $N$  random variables in order to generate  $N$  correlated variables. If  $N$  becomes sufficiently high, the result is that the generated variables converge on the shape of a Gaussian distribution (i.e. central limit theorem), whereas I wanted random uniform distributions to make the results more comparable with other efforts to model riots. The second reason is that I generate the agent hardships in polar coordinates such that I obtain a uniform distribution throughout the unit circle. Using the Cholesky decomposition I obtained hardship values between 0 and 1 in both dimensions, and thus also values that were not within the unit circle. Deleting these values or projecting the square hardship space into the unit circle altered the correlation, and this method ultimately was not suitable for imposing correlations in my model.

Relationships between issues can exist in parallel with segregated communities. For example two minority populations that each live in their own neighbourhoods, can experience similar kinds of strife. Conversely the issues can also be polarised through a negative correlation, where a measure on one of the two issues exacerbates the grief in the other community. Combining correlation in the hardship dimensions and grief segregation between the agents in the two clusters, Figure 5.13 shows that when two communities are heavily segregated ( $\theta = 1/4\pi$  rad), riots mostly spread when the two issues are positively correlated, and the riot frame applies to both communities. However compared to the reference run, the first riot location can compensate for the failure of riot spread under certain conditions; when the issues are negatively related and the riot frame is mostly about issue 1, the total riot activity in cluster 1 is roughly equal to the riot activity of both riot locations in the reference run. Even when the spread of violence can be prevented or does not occur, a single location can still have an extreme impact on the total riot behaviour.

### 5.5.2 Three Riot Locations

Brummitt showed how the patterns of the spread of unrest during the 2011 Arab spring can be distilled into two simplified mechanisms of spread [35]. The first is two neighbouring locations infecting each other (see Figure 5.1), and the second is unrest spreading from one location to another through an intermediary potential riot location which experiences little or no unrest (see Figure 5.14).

Figure 5.15 shows that the second pattern of spread, where a tertiary riot location is infected through an secondary location without any riot activity, is not possible to recreate in the model when only considering segregation and the riot frame. Despite the hardship structure of riot location 3 being the same as riot location 1 with higher levels of segregation, the riot behaviour in location 3 is similar to that of the second location. When increasing the interconnectivity between the riot locations it becomes possible for the third location to break free from the dependence on the second cluster, as shown in Figure 5.16. Such patterns also occurred in the 2011 Arab spring [35], where violence seemed to ‘hop’ over countries that experienced little unrest. The model shows that this pattern can only be achieved at higher interconnectivity between these countries, and only occurs if there is a strong contrast in sentiment between the outer and the intermediary communities.

In this chapter I have focused on riots spreading outward from one location to other locations. Another mechanism of spread that can theoretically occur is ‘reinfection’, where riots are reincited in a location after a period of rest, as a result of activity in another, remote location. Such a pattern is not addressed in this model, as the agents stop attempting to restart the riots the following day once they fail to attract enough participants. However in the real world, a successful emergence of a movement in another location following a locally failed attempt might persuade individuals to persist and reattempt to organise. Such patterns are not addressed in studies of diffusion of violence [16, 17, 131, 132], which like this chapter generally follow a one-way, outwards only, approach to contagion of violence.

### 5.5.3 Spatial Resolution

Different forms of social unrest, including riots, spread on at least three different spatial resolutions; locally within neighbourhoods, regionally between cities, and internationally between countries. In this chapter I have purposely left the nature

## 5.5 Discussion

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of the riot locations undefined and abstract for simplicity, but it is important to understand if, and how, contagion on these three spatial levels is different. As responding to the spread of unrest on these three different scales requires different levels of resources and coordination, it would be interesting to find out if this is also the case for facilitating the spread of riots on these scales.

# CHAPTER 6

## Examining the impact of the spatial and demographic structure of rioters in context of the European migrant crisis

### ABSTRACT

Some riots and protests are specifically related to issues of minority groups. For example Sweden has experienced multiple episodes of civil unrest in the last decade, mostly associated with migrant groups expressing their anger over segregation and social exclusion. The sharp increase in arrivals of asylum seekers in 2015 in Europe following the war in Syria, has led to what is now called the 'European migrant crisis'. As a result of this crisis, the number of asylum applicants has significantly increased in Sweden, as well as in other countries of the European Union. The increased uptake of asylum applicants in Sweden could potentially influence the future probability of violence, given the previous recurrent unrest associated with migrant groups. In this chapter I propose two pathways through which immigration can potentially influence the probability of unrest, and investigate the impact of immigration on riot activity and duration in a numerical model. Additionally I study the effect of social structure between different potential riot groups, and assess the sensitivity to demographic shifts induced by immigration in multiple European capitals to future unrest. I find that; 1) immigration can double the potential riot activity in the model, and 2) that certain strategies to disperse potential rioters over multiple neighbourhoods can initially inhibit potential unrest, but later lead to sharp increases in riot activity as the number of potential rioters grows.

**Author Contributions:** This chapter was written by Jelte Mense, with editorial contributions from Paul Palmer and Matthew Smith.

# 6.1 Introduction

Some riots and demonstrations are framed around issues involving only specific (minority) groups. For example the violence in Baltimore [190], Ferguson [189], and other American cities in the last decade (2006-2016) mainly started after events of (perceived) police brutality against African-Americans. Other events of civil disorder are not uniquely associated with a singular group or community. For example in the 2011 London riots, the people that were arrested consisted approximately equally of individuals with white and black ethnic backgrounds (see Table 2.2), despite both the American and London riots starting with a similar type of trigger, the death of a civilian following police intervention [121]. Instead what seemed to connect arrested participants in the London riots was that 75% of them held previous criminal records [199].

Socio-psychological theories about protests differentiate between movements that are based on structural and incidental issues [221]. Structural issues are those that are based on a group-based disadvantages, while incidental issues are situational, for example a tax increase [221]. A key difference between the two types of movements is that in incidental issues a new collective identity must be formed to recruit people into the movement, whereas in structural disadvantages the collective identity must be transformed [221]. However, the collective identities framed for the recruitment in movements around incidental issues are often built upon existing collective identities [155]. Following this theory it is surprising that the same type of event in the USA and in the UK led to different groups of people involved. Whereas the protests and riots in the USA are focused on improving the position of African-Americans, the London riots involved a much wider variety of the public without a clear orientation or riot frame.

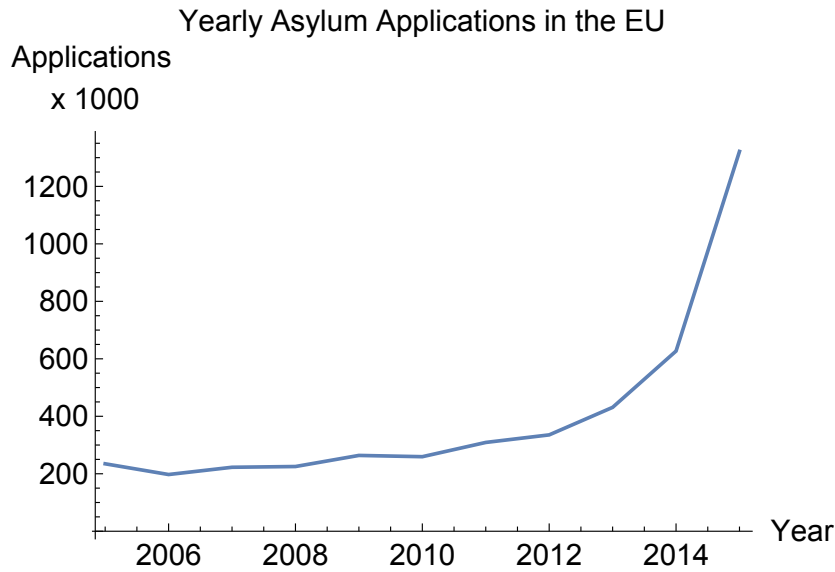
In Sweden, like in the USA, there have been multiple events of civil violence in the last decade (2006-2016) associated with minority groups. The behaviour in the unrest included rioting, stone throwing, and car burning, and mainly involved foreign-born individuals, or took place in areas with high concentrations of non-native Swedish people [114]. The first reports of such incidents involving immigrants started in 2007, and in August 2009 violence spread from Malmö to Stockholm, Göteborg, Uppsala, and other major cities [114]. More recently the 2013 Stockholm riots, that likewise spread to multiple cities in Sweden, also started with the shooting of a civilian by a police officer [170]. Following a protest march initiated by the local political youth

group Megafonen, violence broke out on the 19th of May, lasting more than two weeks [170, 197] (see Chapter 2 for more information). These episodes of unrest in Sweden are believed to be related to social exclusion, segregation, and unemployment [114]. These hypotheses follow from statistical research showing that there are significant links between local unrest such as car burnings, and residential segregation, the number of foreign-born people, proportion of young adults, and welfare assistance [114].

Following the current civil war in Syria, the immigration of asylum applicants into the European union has significantly increased [57, 58], leading to a so-called 'migrant crisis' [126]. One of the causes of the problems in Syria and the resulting emigration is the 2011 Arab spring. The 2011 Arab spring led to unrest in many countries in North Africa and the Middle East. The events varied from protests, for example in Oman [9], to revolutions in Libya and Egypt [7, 8]. The Arab spring also led to a civil war in Syria between several rebel groups and the Syrian government [74]. As part of this ongoing conflict ISIS (also known as Islamic State, IS, ISIL, or Daesh), became an important group fighting both the Syrian government as well as other rebel groups, further increasing conflict in this region [74]. The persistent conflict in Syria has caused a significant portion of the Syrian population to seek refuge in other countries, including neighbouring countries Lebanon, Jordan, and Turkey [206].

By the end of September 2016 the United Nations Refugee Agency (UNHCR) has registered nearly 5 million Syrian refugees, of which 2.1 million are registered in Egypt, Iraq, Jordan, and Lebanon, and 2.7 million in Turkey [206]. Some of these refugees, sometimes facilitated by smugglers, have made successful attempts to cross the Mediterranean Sea in order to establish residency in Europe [91]. The large influx of asylum seekers through illegal channels has forced the EU to come up with a central coordination effort amongst the member states to divide these asylum applicants [162] and reinforce border protection [5].

As a result of this 'immigration crisis' the number of asylum applicants entering Europe has risen significantly [57, 58] (see Figure 6.1). The number of asylum applications in Sweden for example has more than doubled from 2014 to 2015 [57, 58] (See Figure 6.2). The combination of recent and repeated civil disturbances related to migrant groups and segregation in Sweden, and the significant growth of the number of (Syrian) asylum applicants leads to the question of how riots (that relate to minority groups) are established, and how immigration potentially could further influence or exacerbate the probability of riots, including in Sweden and other countries in Europe.

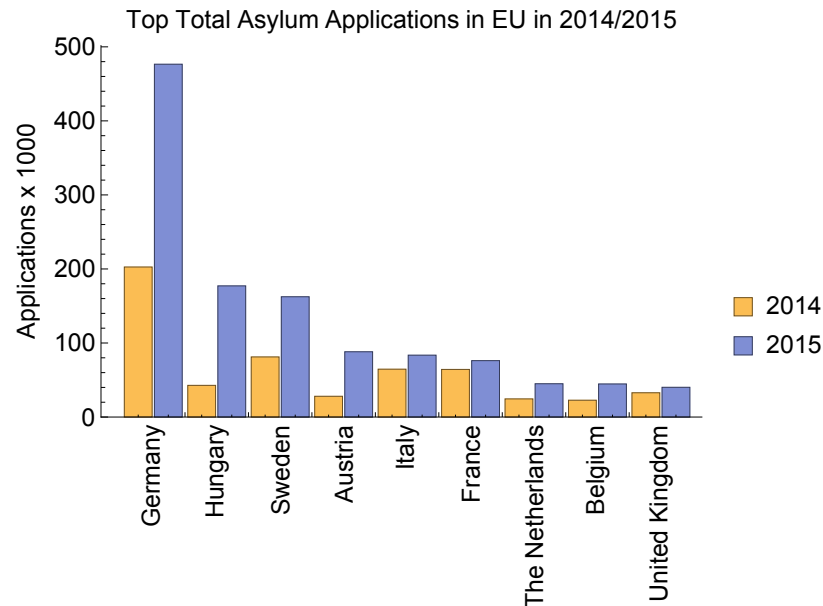


**Figure 6.1: Number of yearly asylum applications in the European Union.** *Based on data from Eurostat [57, 58]*

In this chapter I propose and examine two possible pathways in which the probability of unrest can increase as a result of immigration; 1) grievances resulting from segregation and inclusion in immigrant riot frames and collective identities, and 2) demographic shifts.

The first pathway is association with established migrant groups that have grievances towards the host country. The main immigrant groups outside of the EU in Sweden come from Syria, Somalia, Eritrea, Afghanistan, and Iraq [181]. If the structural issues that caused the previous unrest in Sweden have not been resolved, and the new incoming asylum applicants experience similar types of strife to previous or existing migrants, they might associate with riot frames that describe discontent about these issues. Effectively they might form coalitions with existing migrant groups, by being included in riot frames that encapsulate all minority immigrant groups rather than just those of a specific ethnicity. This would increase the potential number of rioters, which could lead to a higher probability of unrest, as previous research has shown that the main predictor of racial violence in the 1960s in the USA was the local concentration of minorities [178, 179, 180].

This reasoning is not exclusive to the current incoming group of asylum applicants, or to migrants with a specific ethnicity. The earlier unrest in Sweden for example, has not been reported to be exclusively related to a specific ethnic group



**Figure 6.2: Number of asylum applications per country in the EU in 2014 and 2015.** Only the nine countries with the highest application counts are shown. Based on data from Eurostat [57, 58]

[191]. However, the synchronous arrival of many migrants with the same ethnicity, and potentially the same or shared traumas, could lead to the formation of strong local communities [150]. A stronger collective identity fosters collective actions of protest, leads to stronger emotions of grief, and increased (perceived) group efficacy [92, 184, 221]. The concurrent arrival of many asylum applicants with the same ethnicity might therefore lead to a higher probability of unrest if this group experiences similar grievances as previous migrant groups, even if the structural problems for these other existing migrant groups are already solved.

The second pathway by which the probability of unrest can increase is through demographic shifts. Initially the media reported that the arriving refugee groups were predominantly made up out of young adult males (e.g. [83]), potentially to prevent conscription into local armed forces. The destination countries of these migrant groups in Europe, like Germany, the Netherlands, and Sweden, are generally in transitioning towards an ageing population [45, 73], as a result of high number of births after the second world war in combination with improved health care and living conditions [73, 113]. The problem of ageing populations is one of the reasons why Germany (initially) welcomed the arrival of asylum seekers with open arms [52].



## 6.1 Introduction

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Previous research has stressed the relation between the age composition of a population and the likeliness of conflict (e.g. [45]). The incidence and frequency of conflict is highly linked to so-called 'youth bulges', an age structure that describes an overrepresentation of individuals between the ages of 15 and 29 (>40%) [45]. Especially males in this group, combined with poor socio-economic opportunities, are more prone to engage in violence [45, 78]. Moreover males are also more susceptible to manipulations of social identity [175], which could make them more likely to respond to riot frames. Examining the age structure of the main refugee groups in Sweden (Syrians, Somalians, Afghans, and Iraqis) reveals a minor youth bulge in these groups (36%), that is absent when analysing the total population of Sweden. The total size of these groups might be small compared to the total population of Sweden, but might be large enough to create a significantly different localised population structure that influences riot behaviour. Such a 'hidden' youth bulge might be one of the reasons why the riots that broke out in Sweden were such a surprise [145]. The current influx of asylum seekers on such a large scale could introduce or exacerbate similar localised population structures, which might make such communities more prone to instigate or engage in civil unrest.

Both pathways are dependent on underlying structural problems: immigration and demographic shifts alone will not introduce a risk of violence, but could exacerbate potential existing issues like social exclusion and segregation. Additionally the second pathway also acts as a catalyst for the first pathway, as association with the grief of other groups and inclusion of riot frames combined with the specific age groups that are linked to conflict could further increase the probability of unrest.

The current immigration might influence the probability of unrest recurring in Sweden, especially if the underlying issues from earlier outbreaks of violence are not resolved. Additionally the rise in number of asylum applications to other European countries could introduce or increase susceptibility to civil unrest in other locations. The large number of incoming asylum applications can lead to a strain on the resources of the immigration services that guide them in their new host countries (e.g. [44]). As a result there have been minor protests in the Netherlands by some asylum seekers, expressing dissatisfaction regarding their temporary shelters and housing (e.g. [10, 146]). If such resource shortages become structural, then the integration of these groups might fail, potentially leading to similar problems as the past unrest in Sweden.

The main question of how riots are established and how the probability of

unrest is influenced by immigration is addressed through the following subquestions: 1) How does the number and the spatial distribution of potential rioters in cities influence riot activity, probability, and spread? 2) How does the distribution of different riot groups and overlap in hardship influence riot dynamics? 3) How do demographic shifts induce or change the risk of unrest?

The nature of this chapter is exploratory, as I try to apply the model to simplifications of urban environments and hypothetical future situations. Although the term immigration describes the settlement of any foreign-born individual, in this chapter it specifically applies to those seeking asylum in European countries, as I address the research questions in context of the current 'immigration crisis'. The claim of this chapter is not that such immigration only has negative consequences, and will always lead to riots or increase risk of unrest. Instead I recognise and explore two pathways through which immigration possibly relates to civil unrest. There are many more ways in which the arrival of immigrants can have both negative and positive effects, but the focus of this chapter is to explore and understand sensitivities of unrest to immigration, for example through demographic shifts. The methodology and experiments that I use in this chapter to answer the research question are not specific to immigration only, and consequently lead to results that have much wider applications.

## 6.2 Model

I use an agent-based model to answer the research question of how riots are established through the number of rioters and their spatial dispersement, and the potential influence of demographic shifts, and under which conditions different riot groups are prone to form coalitions. The model that I use in this chapter is the same as the model described in Chapter 3. A summary of the model description without the motivation for the model design can be found in Appendix 8.7.

## 6.3 Methods

In this chapter I focus primarily on unrest within single cities. Although violence can spread between cities (e.g. London 2011 and Stockholm 2013), and even between countries (Arab Spring 2011) the conditions under which such diffusion occurs are addressed in Chapter 5. To study the probability of unrest in urban environments and account for the spread and diffusion of violence within cities I describe multiple riot locations. The main methodological differences between the methods used in this chapter versus those in Chapter 5 is that in Chapter 5, each location is associated with a distinct population of agents, whereas in this chapter I mix agents with different types of hardship within the same locations. Chapter 5 therefore relates more strongly to spread between countries, where for example grievances are related to the specific government of that location, and the overlap in issues between the two countries causes the riots to spread. Conversely in this chapter agents with different hardship structures are mixed within the same location, reflecting divided communities that are living together within countries and cities, for example two different minority groups.

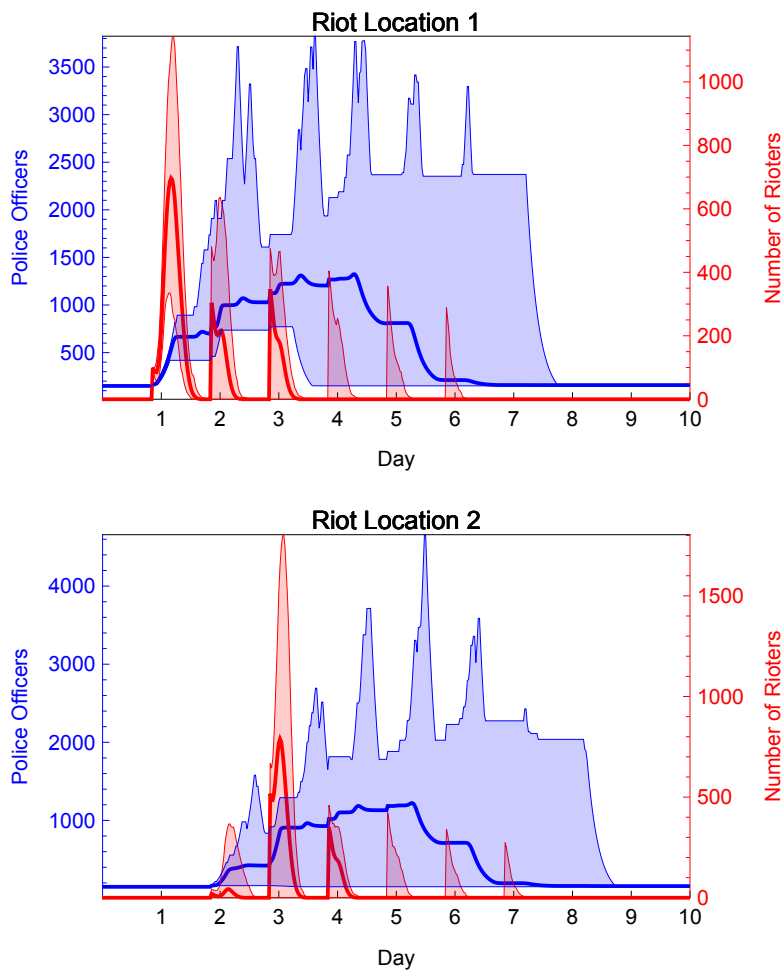
I simplify city geography and layout to six potential riot locations. The riot locations are represented by agent clusters. Each cluster is generated by its own small world network algorithm, with a minor modification to link the clusters together (see Section 3.5). Six of these clusters offer sufficient interactivity between riot locations while also keeping the dynamics of spread traceable and simple enough to study.

To explore the sensitivity of future unrest I establish a ‘reference’ model run, which I use as a reference point to compare changes in the model, for example a different number of rioters or group allocation over different locations. In this chapter I combine the model approaches of Chapters 4 and 5; I describe multiple, coupled riot locations while also targeting a specific real-world location. The standard or reference model run is based on Stockholm, by assigning the ages of the agents according to the age distribution of the Stockholm population [181]. I run the model at each parameter setting 1,000 times to obtain an ensemble of behaviour, from which I obtain metrics that I compare back to the reference model run.

Figure 6.3 shows the model behaviour for the reference model run in the six riot locations. The parameter settings for the reference behaviour are listed in Table 6.1. The riot starts in the first cluster, and then spreads to the other five clusters, of which only one is shown. The behaviour in the remaining five clusters to which the riots

## 6.3 Methods

spread is the same, because in the reference run the populations in all the locations are based on the same age distribution. The riot starts on the first day in the first riot location, and spreads to the other clusters on the second day. In all locations the median riot lasts three days, leading to a total riot duration of 4 days because the riot starts a day later in the secondary agent clusters.



**Figure 6.3: Reference model run showing riot and police activity in two riot locations.** The number of rioters (red) and number of police officers (blue) in riot location 1 (top) spreads over to location 2 (bottom). The riot activity in the remaining clusters that are not shown is identical to the activity of the second cluster. The median number of rioters and police officers is shown in bold, and the variance is shown in the faded background.

Symbol	Description	Units	Value
$N$	Number of Agents	Agents	30,000
	Number of Riot Locations	Locations	6
	Riot Location Cluster Size	Agents	5,000
$2k$	Number of Agent Connections		32
$p$	Rewire Probability		0.2
$q_{\text{out}}$	Rewire Probability Out		0.33
$N_{R0}$	Riot Start Size	Agents	100
	Riot Start Time	Hours	20
$\alpha$	Communication probability		0.5
$\omega$	Memory capacitance	$t^{-1}$	0.5
$\beta$	Network control 1		0.15
$\gamma$	Network control 2		2.5
$\delta$	Deterrence	Rioters/Police officers	1
$\varepsilon$	Fatigue		0.13
	Cooldown	Hours	12
$\theta$	Segregation Angle	Degrees	0
$F_\phi$	Riot Frame Angle	Degrees	45
$P_{\text{min}}$	Initial Police per Location	Officers	150
$P_{\text{max}}$	Maximum total Police	Officers	5000
	Fraction of Agents with randomly assigned Age	% Agents	20

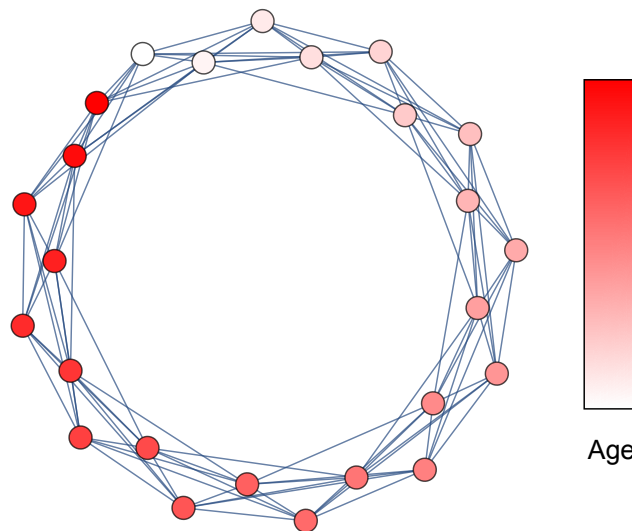
Table 6.1: Model parameter values for reference run.

### 6.3.1 Age Distributions and Structure

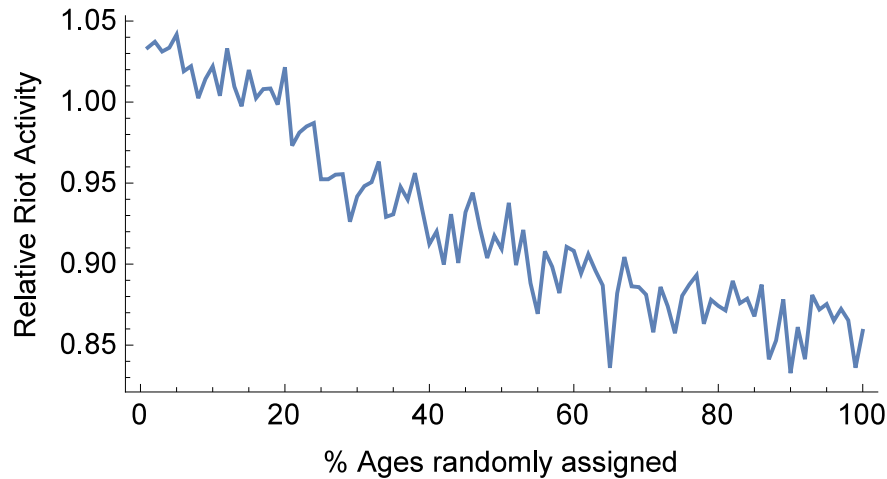
The clusters that represent riot locations are generated using a small-world algorithm. The agents are first placed on a ring lattice, after which they all connect to their  $k$  nearest clockwise neighbours. Each of these connections are then rewired with probability  $p$ , the rewire probability, which describes the degree to which the network is a random network. Each rewired edge is wired to another cluster with probability  $q_{\text{out}}$ , rather than to another node within the same cluster.

I use the initial ring structure of the network to make agents more likely to be connected to agents of similar ages [49], by sequentially assigning the ages on the ring lattice, as shown in Figure 6.4. Because in the reference runs, the number of rewired edges is 20% (see Table 6.1), the ring structure is largely left intact. The approach that

I use however has a disadvantage that at the top of the ring structure, several of the youngest agents are also connected to the oldest agents. A better approach would be to assign the agents outward in both directions simultaneously, instead of only clockwise or counter-clockwise, as shown in Appendix 8.8. The result would then be that the top half of the ring contains the younger agents, and the elderly are placed at the bottom of the ring. For 20% of the agents in the network, I reassign an age stochastically drawn from age distribution of the area under investigation, to reduce the strong structure imposed by the sequential allocation of the ages. Figure 6.5 shows the effect of age mixing in the model, where I demonstrate the effect of the percentage of agents that is assigned a random age on the riot activity. The age structure in the network has a limited, positive effect on riot activity: connections to similarly aged agents lead to heavier riots.



**Figure 6.4: Example of structuring information in a network cluster.** *The age of the agents is structured along the ring lattice generated by the small-world network algorithm.*



**Figure 6.5: The effect of age structure in the network on riot activity.** *The ages in the model are originally distributed along the ring lattice in each riot location, as shown in Figure 6.4. Then a percentage of the population is randomly reassigned another age according to the underlying age distribution, dependent on the location under investigation. The x-axis shows the percentage of agents that have a randomly assigned age, the resulting riot activity is shown on the y-axis. The riot activity is expressed relative to the reference run (Figure 6.3), in which 20% of the agents have a randomly assigned age.*

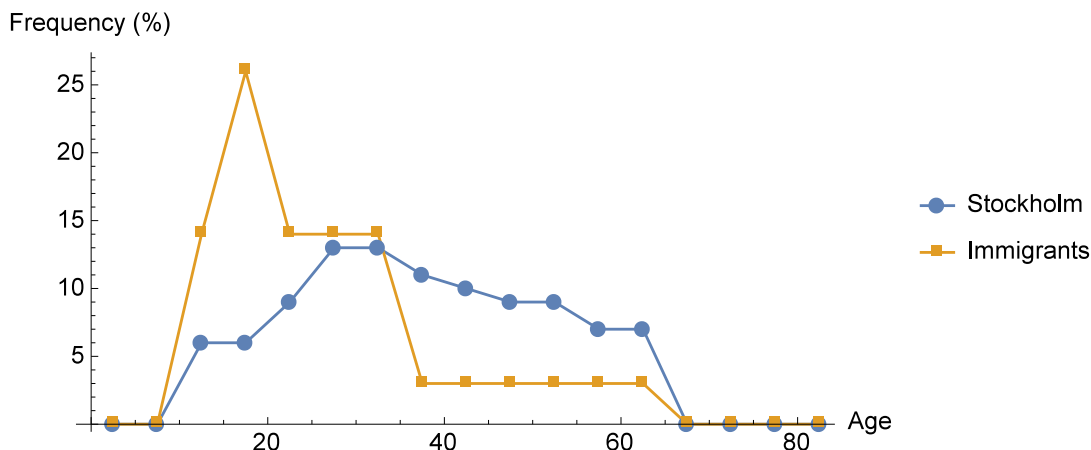
To study the effect of collaboration between different groups and immigration in the model I define two separate agent groups. The first are ‘resident’ agents, that represent the current population, such as established minorities and the native inhabitants of a country. The second group are ‘immigrant’ agents, which are mixed into the resident group of agents by replacing them, representing the process of immigration. The reason that resident agents are replaced by immigrants is that at some stage of the application process for asylum, refugees are appointed housing that in general, could have been used otherwise by individuals that are existing residents of the host country. The main two differences between the two groups are the age structure of the two populations, and the issues they can be aggrieved about, further described in Section 6.3.2. These groups are framed and defined in the context of potential riots related to immigration, but without the age distributions reflect abstract groups that could also be related to other types of populations and riots.

The age distribution of the immigrant agents is based on data from Eurostat, the statistical office of the European Union (EU), and UNHCR [57, 58, 206]. However, both organisations record the ages of incoming migrants in broader age bands than is customary within the individual member states of the EU, which I use to distribute the ages of the agents in the model. Generally the population is divided into age bands of at most, 5 years (e.g. [85, 181, 182, 200]), and in some cases the contributions towards



the total population can be expressed for each yearly age [43]. The agebands used by UNHCR and Eurostat are 0-13, 14-17, 18-34, 35-64, and 65+ [57, 58, 206].

In the model the ages of the agents are assigned using 5 year increments. The ages of the immigrant agents are based on the age distribution of immigrants coming into Sweden [57, 58]. To use this data I convert the wider and irregular agebands to 5 year increments. The relative age frequency of the immigrants are divided by the width of the age bands from the UNHCR to obtain a frequency for each yearly age, and from those I construct a new age histogram using fixed 5 year increments. Figure 6.6 shows the resulting age distributions that I use for both the resident and the immigrant agents in the model, based on the population of Stockholm [181] and asylum applicants coming into Sweden [57, 58]. Following the arrest records of the London riots [121, 127, 161], I only consider rioters between the ages of 12 and 65 in the model.



**Figure 6.6: Age distributions used in the model.** The age distribution of Stockholm [181] is shown in blue, the immigrant age distribution [57, 58] in yellow. The model only describes potential rioters, such that the ages are limited between 12.5 and 62.5.

### 6.3.2 Segregation of Hardship

Similar to Chapter 5, the grief or hardship of the agents is expressed along two dimensions. Each dimension describes a separate, independent issue about which the agents can be aggrieved. Like in Section 5.4.3 in the previous research chapter, I define a *segregation angle*  $\theta$ . In Chapter 5  $\theta$  describes the difference in grievances between two communities based in two different locations. In this chapter  $\theta$  also represents the

segregation angle, but here it is used to describe the difference in grief between two types of agents, which can be located in the same cluster. The two types of agents are the resident and immigrant agents, that have different age structures. Resident agents represent established citizens, including those who might have migrated a longer time ago. Based on the data that I use for the age distribution for the immigrant agents, they mainly represent the group of currently arriving asylum applicants.

The value of the segregation angle  $\theta$  ranges from 0 to 90 degrees. If  $\theta$  is 0, there is no segregation of hardship and both populations can experience grief about both issues. At a segregation angle of 90 degrees, the resident agents are only aggrieved about issue X, and the immigrant agents only about issue Y. These two issues are expressed along the two hardship dimensions.

### 6.3.3 Placement of Rioters

One of the questions addressed in this chapter relates to the influence of the placement of rioters and the distribution of different riot groups to riot activity. In some cases, for example, rioters might be very closely connected, forming a localised cluster within a riot location. In such a case they would likely join as a group, due to their high interconnectivity. Conversely if the rioters are more spread out through the network, they can disseminate knowledge about the riot faster and consequently potentially mobilise a larger group of participants within a shorter amount of time. This subsection describes the setup of the two main experiments, that relate to the placement of rioters in the contact network. Besides the placement of rioters, there is also the replacement of resident agents by immigrant agents. I define four different ways to distribute the immigrant agents over the different riot locations, and two additional mechanisms to distribute them within the individual riot locations.

In the first experiment I investigate how the sequential introduction and placement of rioters establishes a riot and influences further dynamics. I start by setting the hardship of all agents to zero in both dimensions, and then I add agents with regular hardship levels one by one to study how the riot is initiated. The second experiment is similar, but there I discriminate between the two types of agents described in the previous subsection, the resident and immigrant agents. Upon initialisation of the model all agents are described as resident agents, which are consequently replaced by incoming agents with a different hardship to study when the two groups form coalitions. Thus in the first experiment, passive agents are replaced

by agents that are willing to riot, whereas in the second experiment resident agents are replaced by immigrant agents, with different grief and age structures, and both agents are willing to join riots from the start.

In both experiments I use different mechanisms to distribute and replace agents. These mechanisms take place on two different levels; the first describes how incoming agents are distributed over the different riot locations, whereas the second level describes how agents are replaced within a selected riot location. I distribute the incoming agents in the two experiments in four different ways: 1) Sequential, 2) Limit, 3) Equal, and 4) Random. These mechanisms describe the way in which the agents are divided over the six clusters, consisting of  $N$  agents in total. In *sequential* distribution,  $m$  incoming agents are distributed such that the first  $\frac{N}{6}$  are placed in the first location, the second  $\frac{N}{6}$  of  $m$  in the second location etc., such that each location is filled with incoming agents until all agents in that cluster have been replaced.

The *limit* mechanism is similar to sequential distribution, as the agents are sequentially distributed over the different riot locations. The difference is that in the limit mechanism, each location is first filled up to the pre-set limit instead of the full capacity of the cluster, after which the next agents are assigned to a different location. In this chapter I set this limit to 50% of the cluster size, such that all agents are replaced in two sequential rounds. In *equal* distribution  $m$  incoming agents are equally divided over the six clusters, and in *random* distribution the cluster is randomly allocated using the Fisher-Yates shuffle [59], introduced in the next paragraphs.

The reason for implementing the limit distribution mechanism is that research on segregation shows that there are certain thresholds within neighbourhoods on diversity [41]; if minorities become too prevalent in a neighbourhood, the native and resident white population leaves. Examinations from census tract data in the USA identify these thresholds at between 5 to 20% minority share, but can be higher in areas where there are more tolerant racial attitudes [41]. Likewise Schelling's model of segregation also shows signs of 'tipping' behaviour, where the dynamics of segregation quickly change once the model passes a certain threshold [169]. Although such mechanisms are not explicitly present in my model, the optimal way to distribute immigrant agents in the model using a sequential distribution would then be to only allow immigration in the riot locations up to the thresholds, which can be achieved using the limit distribution mechanism.

The four mechanisms describe how the agents are divided over the six clusters

that together represent potential riot locations within a city. Within these clusters I replace agents in two different ways: 1) sequential, and 2) random. The difference between these replacement mechanisms and the previously listed distribution mechanisms is that I now describe how agents are replaced within riot locations, whereas the previous mechanisms describe how agents are distributed over the different locations. In *sequential replacement*, the resident or passive agents are replaced counter-clockwise on the ring lattice by incoming agents. When the rewire probability  $p$  is low, these agents are then more likely to be connected to each other and form a closely knit group. In my experiments I do not combine this local replacement mechanism with global random distribution of agents to different locations.

The second mechanism to locally replace agents within the cluster is *randomly*, by using the Fisher-Yates shuffle [59]. The Fisher-Yates shuffle can be used to rearrange the sequence of numbers between 1 and  $N$  in a random order. This is equivalent to using a random uniform distribution to decide to replace which agent within a cluster, with the added benefit that there is no need to keep track of which agents have already been replaced to prevent changing an agent twice. Moreover when using random global distribution in combination with random local replacement (over and within the riot locations) I only have to shuffle once, rather than on two spatial levels.

In the second experiment, where resident agents are replaced by immigrant agents, I also include an alternative setup in which the counter-clockwise direction in the local sequential replacement is reversed. Due to the age structure within the riot locations described in the beginning of Section 6.3 and Figure 6.4, the normal (counter-clockwise) sequential replacement of agents reverses the age structure of the agents in the cluster, as older resident agents are replaced by young immigrant agents. At low levels of immigration this direction of replacement has maximum impact, and I therefore include and compare with a clockwise replacement to discern the differences between where immigration takes place.

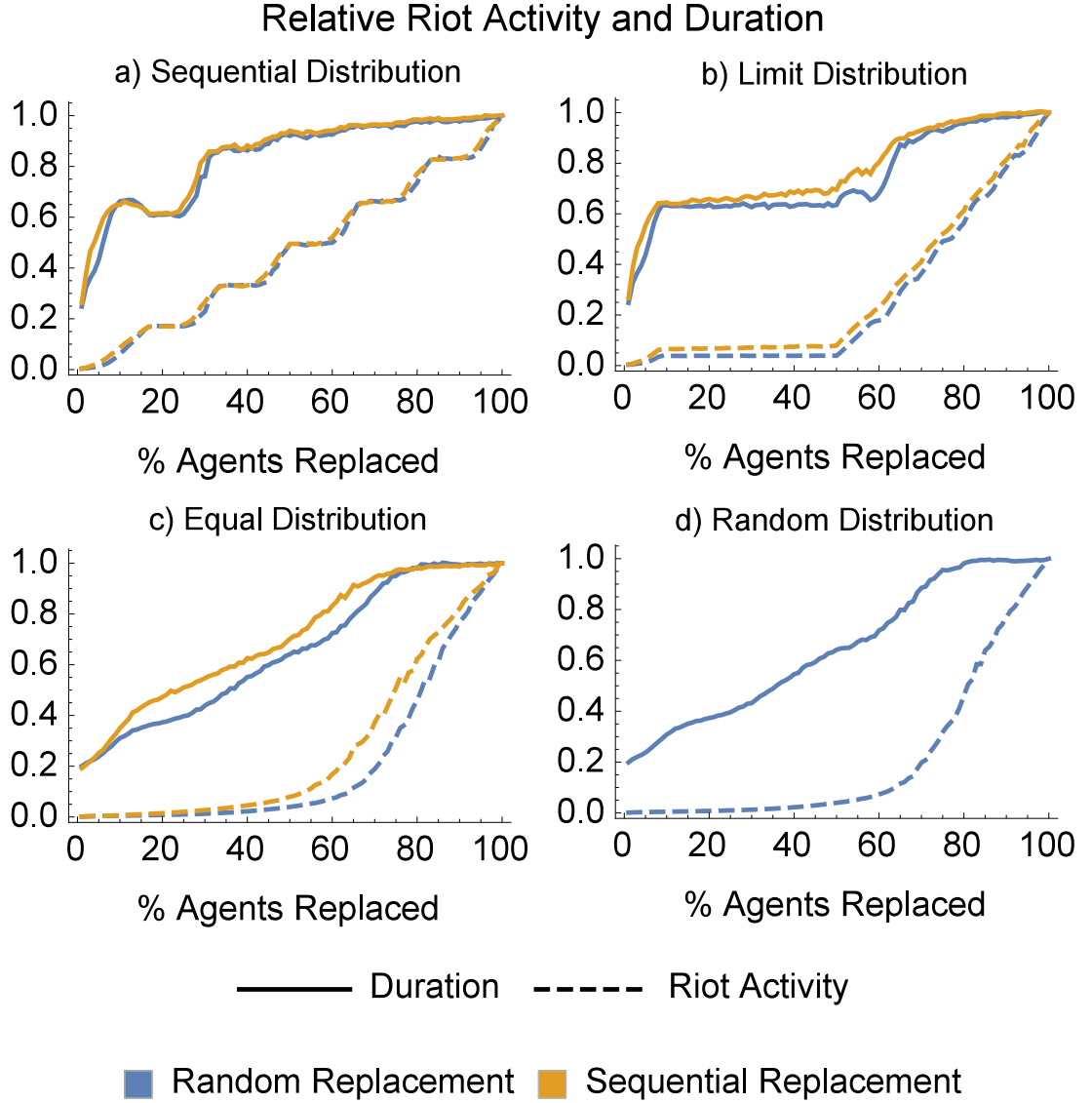
## 6.4 Results

I study the impact of immigration on riot dynamics by addressing the three following questions: 1) How does the number and the distribution of potential rioters in cities influence riot activity, probability, and spread? 2) How does the distribution of different riot groups and overlap in hardship influence riot dynamics? 3) To what degree are riots more likely due to the current influx of migrants through association and demographic shifts?

### 6.4.1 The Effect of Social Structure of Rioters

The dynamics of a riot, such as the total activity, spread, and duration, are dependent on the number of individuals that facilitate and are willing to participate in these events. To study how riots are established as a result of number of potential rioters, I first consider the situation in which none of the agents has the desire to join (passive), and then sequentially replace them by agents that are aggrieved (active). The different approaches I use to replace passive by active agents are described in Section 6.3.3. The age distribution for the active agents is the age distribution of Stockholm [181] (Figure 6.6), such that when all passive agents are replaced the settings are the same as in the reference run (Figure 6.3).

Figure 6.7 shows the riot activity and duration as a result of different distribution (global) and replacement (local) mechanisms and number of rioters. The distribution mechanisms correspond to the way in which active agents are placed in different neighbourhoods, e.g. all in the same area or equally divided over all the riot locations. Within these areas the passive agents are then replaced randomly or sequentially along the ring lattice by active agents, the latter making the active agents more likely to be connected to each other.



**Figure 6.7: Effect of the number of rioters and their spatial distribution on mean riot activity and duration.** Relative mean riot duration (solid) and activity (dashed) is shown along the y-axis under the influence of the number of rioters. Passive agents that do not participate in the riot are replaced by active agents. The relative proportion of agents that is replaced is displayed on the x-axis. The rioters are distributed differently over the clusters: a) Sequential, b) Limit, c) Equal, and d) Random, as described in Section 6.3. Within the riot locations the rioters can be replaced sequentially along the network lattice (yellow) or randomly (blue). The riot activity and duration are expressed relative to the reference run (Figure 6.3).

The local sequential replacement of passive agents within the clusters results in a longer and more active riot than the random mechanism, regardless of how the active agents are distributed over the different riot locations. Both replacement mechanisms result in similar patterns for riot activity and duration as a result

of the number of active rioters. The differences between sequential and random replacement are smallest and insignificant when agents are sequentially distributed over the riot locations (Figure 6.7a), and are largest when using the equal mechanism (Figure 6.7c). The largest difference in riot activity between sequential and random local replacement is 30%, and occurs when distributing agents equally over the riot locations (Figure 6.7c), when 75% of the passive agents are replaced.

The sequential replacement mechanism results in more and longer riot activity because the active rioters are placed more closely together in the network, increasing the probability that they are connected to each other. This leads to pathways that enable more riot activity; first the knowledge of the riot travels more quickly between the localised cluster of agents. Secondly, these agents increase the propensity of each other to join the riot as each subsequent member of the connected group members decides to participate, making them join in groups over a couple of iterations. These two pathways are embedded in the design of the experiment and the model, and apparently from the result these local ties are more important than the long range ties that could help spreading information about the riot faster through the clusters.

Figure 6.7 also shows the effect of the different distribution mechanisms that describe how the agents are divided over the clusters. When no agents are replaced, the total riot activity is zero as all other agents are passive. The riot duration is still 20% of the reference run (1 instead of 5 days), despite that the propensity of the agents to join is zero. This is caused by the way in which I start the riot; I select  $N_{R0}$  agents randomly to participate in the start of the riot proportional to their grief. After these  $N_{R0}$  agents are placed in the riot, the grief of these agents plays no further role in deciding when to leave, leading to a one day riot.

The sequential distribution mechanism causes the fastest initial increase in both duration and total riot activity (Figure 6.7a) as more active agents are added. The shape of the riot activity clearly marks the six riot locations as the passive agents are replaced. The duration mainly increases as a result of the first 10-20% agents that are replaced. Adding more rioters to the other riot locations causes diminished further increases in duration. The duration initially goes up when adding rioters to the first cluster, but then shortens as the police intervenes. The police at this stage has many resources still available, and they are able to shorten the duration of the riot as they increasingly respond to the larger number of rioting agents.

First replacing half of the agents in each location, as done in the limit distribution

mechanism (Figure 6.7b), leads to a similar initial increase in riot duration compared to the sequential distribution of incoming agents. The riot activity however, does not significantly increase like the duration, up until 50% of the passive agents have been replaced by active rioters. When the second part of the network cluster in each riot location is replaced by the active agents, the riot activity quickly increases in a straight line towards the riot activity of the reference run.

Equal and random distribution result in similar shapes to each other (Figure 6.7c and d). The duration increases roughly in a straight line, and reaches the same duration of the reference run after around 70% of the passive agents have been replaced. There is no difference between using equal distribution in combination with local random replacement, and the fully random replacement of agents anywhere in the network. Like the limit distribution mechanism, the riot activity remains low initially, and increases more strongly after more than half of the passive agents have been replaced.

### 6.4.2 Demographic Shifts

One of the subquestions in this chapter is how age and demographic shifts, for example induced by immigration, influence riot dynamics. To answer this question I use the same basic setup as in the previous experiment, but instead of substituting passive by active agents, I replace ‘resident’ by ‘immigrant’ agents. The main difference between the two groups is the age structure of the two populations. The ages of the resident agents are distributed according to the age distribution of Stockholm [181], whereas the ages of the immigrant agents are distributed according to the age distribution of immigrants arriving in Sweden [57, 58]. Both age distributions are shown in Figure 6.6, and how they are obtained is described in Section 6.3. Unlike the previous experiment, both groups are willing to join the riots, such that the situation where none of the resident agents are replaced corresponds to the reference model run described in Section 6.3 (Figure 6.3). The change from resident to immigrant agents induces a demographic shift, which is likely to increase riot activity due to the different age structures and the boost in grief in agents between the ages of 15 and 29. I use different mechanisms to select which agents are replaced, and investigate the effects of the spatial distribution of immigrant agents in the network on riot activity and duration, compared to the reference model run. The selection mechanisms by which I replace resident by immigrant agents are detailed in Section 6.3.3.

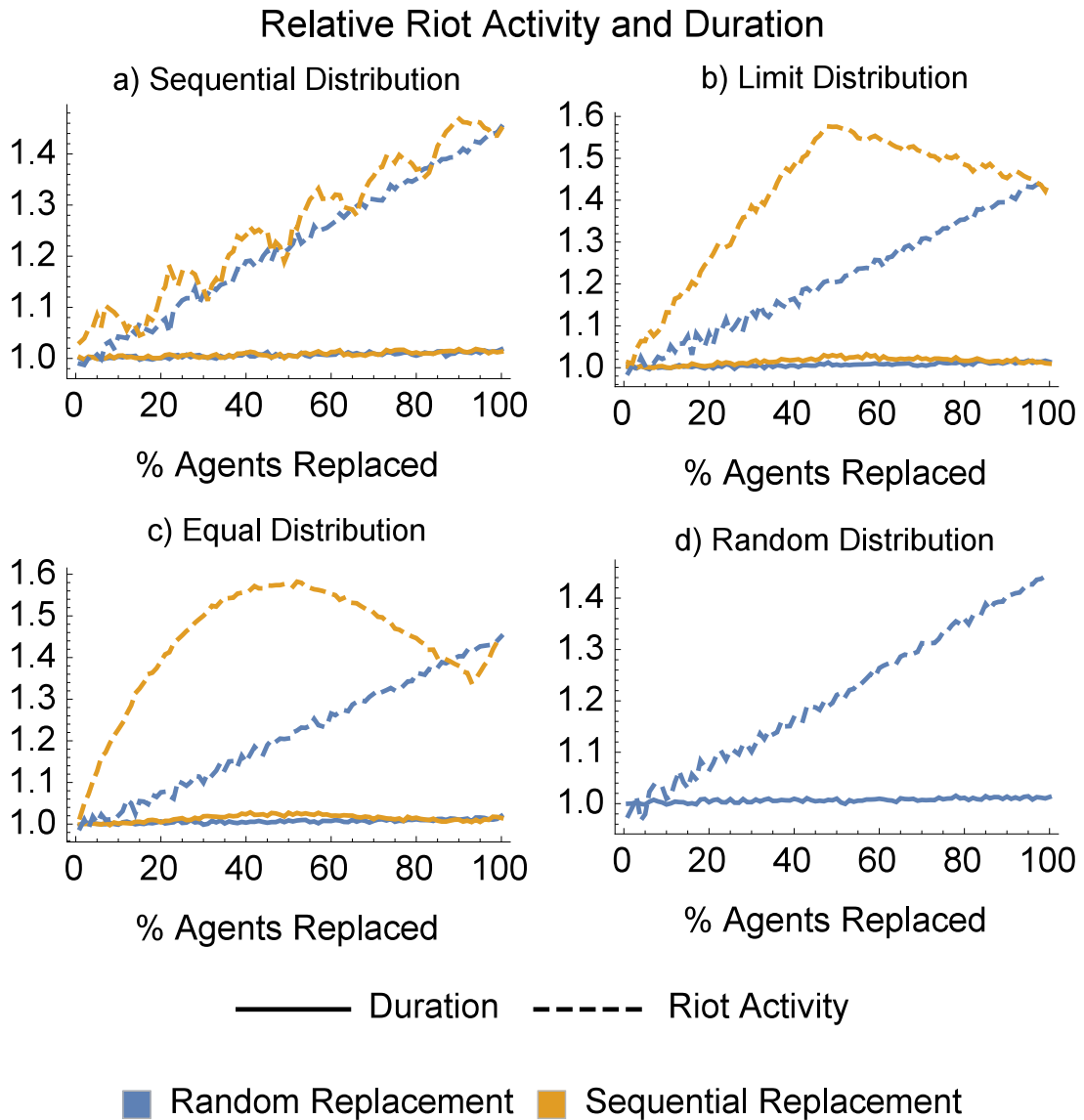


Figure 6.8 shows the effect of replacing resident agents with immigrant agents, compared to the reference run. The duration of a riot is not or barely influenced by the different age structures of the agent populations in any of the distribution and replacement mechanisms. The riot activity increases by 45% when all resident agents are replaced. The different age structure (Figure 6.6) combined with the age amplification factors (Section 3.4) make the immigrant agents more likely to join the riot compared to the resident agents, increasing the riot activity. This increase occurs in a straight line when the immigrant agents randomly replace resident agents within the locations, regardless of how the incoming immigrant agents are distributed over the different riot locations.

The sequential replacement mechanism of agents within the riot clusters of agents generates different results than the random replacement: when incoming agents are sequentially distributed over the riot locations the riot activity initially increases as the older resident agents are replaced by younger immigrant agents, and consequently falls again when the youngest residents are replaced by the oldest immigrants (Figure 6.8a). Overall the riot activity steadily increases, and the rising and falling pattern repeats as each the agents in each cluster are sequentially replaced. This effect is globalised for all riot locations in the remaining limit and equal distribution mechanisms (Figure 6.8b and c), leading to a maximum increase in riot activity of 60% compared to the reference run.

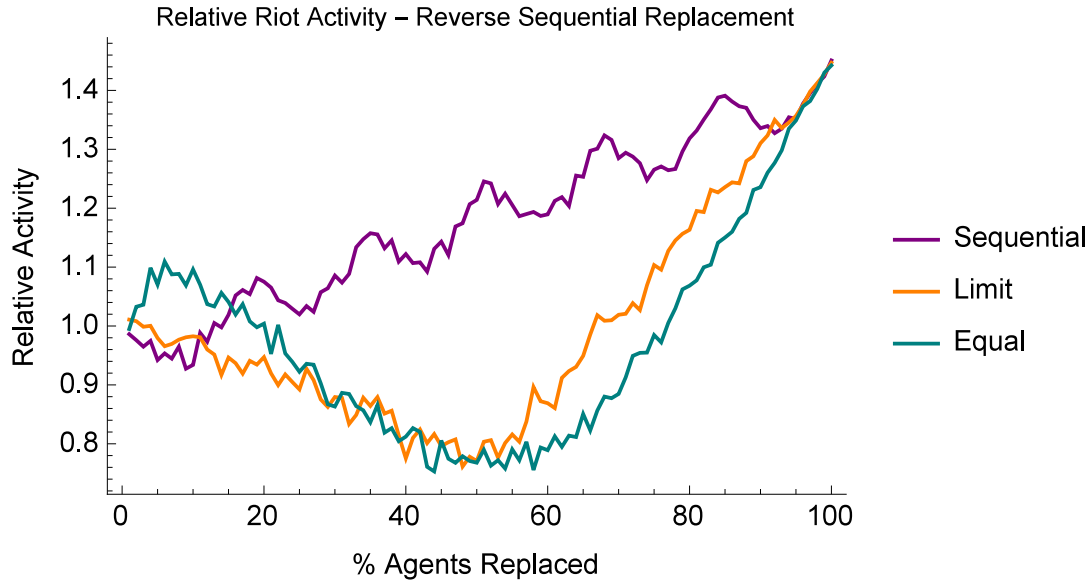
If the resident agents are replaced sequentially within the clusters, the direction of the replacement matters due to the age structure of the resident agents within the network cluster (see Section 6.3). Figure 6.9 shows the effect of reversing the direction of replacement (clockwise), such that the younger resident agents rather than the elder are replaced first. In addition to the direction of replacement, the initial starting point across the ring lattice matters as well. In this chapter I only address the two directions, because they represent distinct scenarios in which certain parts of the population get replaced first by immigrants.

When distributing the migrant agents sequentially over all the riot locations (Figure 6.9), reversing the direction of allocation leads to a partially inverse pattern. The increasing trend in riot activity remains as resident agents in whole riot locations are replaced, but within those clusters the riot activity first drops and then increases, the opposite of the pattern in Figure 6.8a. This inverse pattern is caused because of the different age structures, as the resident agents who are most prone to join



**Figure 6.8: Influence of demographic shifts and spatial age differences on riot activity and duration.** Resident agents are replaced by immigrant agents, which have different age structures shown in Figure 6.6. The relative mean riot duration (solid) and activity (dashed) is shown along the y-axis, under the influence of the relative number of replaced agents displayed on the x-axis. The immigrant agents are distributed differently over the clusters: a) Sequential, b) Limit, c) Equal, and d) Random, as described in Section 6.3. Within the riot locations the resident agents are replaced sequentially along the network lattice (yellow) or randomly (blue). The riot activity and duration (y-axis) are expressed relative to the reference run (Figure 6.3).

the riot (ages 15-29) are replaced first. Likewise the pattern for riot activity for the limit and equal distribution mechanisms are also inversed as a result of the different



**Figure 6.9: Effect of replacing resident by immigrant agents in opposite sequential direction along the ring lattice.** Percentage of resident agents replaced by immigrant agents ( $x$ -axis), in the opposite direction (clockwise) such that young resident agents are replaced first rather than last. The immigrant agents are distributed according the 1) Sequential (purple), 2) Limit (orange), and 3) Equal (green) distribution mechanisms described in Section 6.3. The relative riot activity ( $y$ -axis), is expressed relative to the reference run (Figure 6.3).

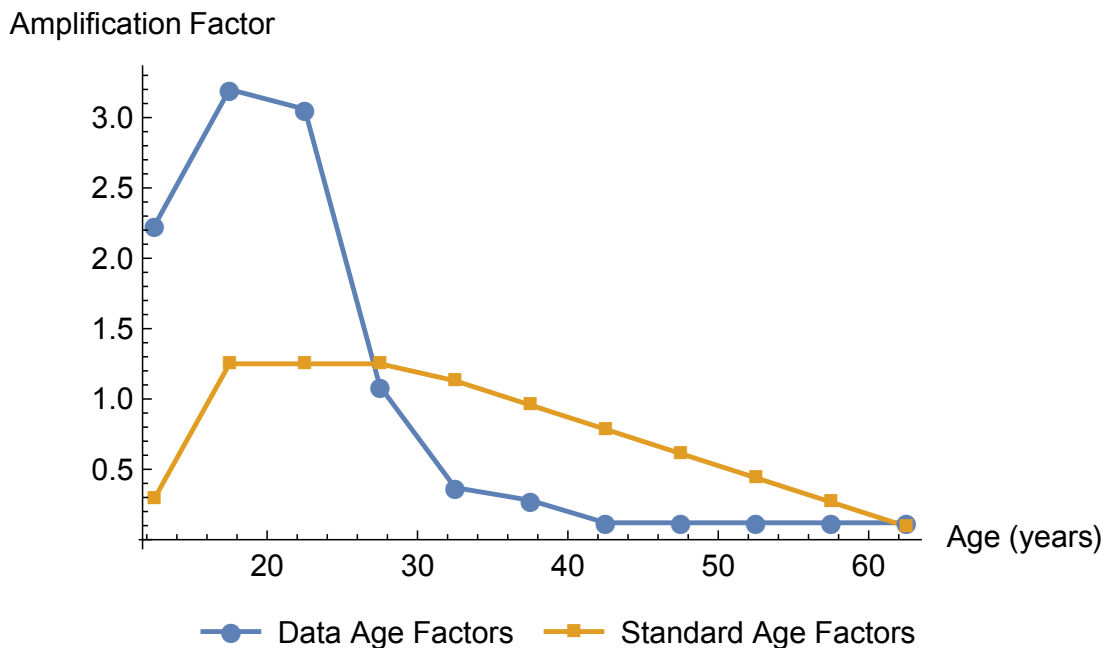
replacement direction, as shown in Figure 6.9. Instead of first increasing to 160% riot activity compared to the reference run and then decreasing to a final 145% as all the resident agents are replaced, now the riot activity first drops by more than 20%, after which it increases to the same 145%.

### 6.4.3 Age Sensitivities Based on Data

The propensity of the agents to join the riot partially depends on their age. The age dependence is included in the model based on research that has shown strong relationships between the incidence of conflict and certain age structures, particularly so-called *youth bulges* [45]. According to the definition stated by Cincotta, a population has a youth bulge when at least 40% of the population is between the ages of 15 and 29. To account for this effect I convolve the hardship of the agents, their primary motivator to join the riots, with an age-dependent factor detailed in Section 3.4, and in more detail in Section 3.4.

The age-factors in the model are set such that generally the hardship of agents

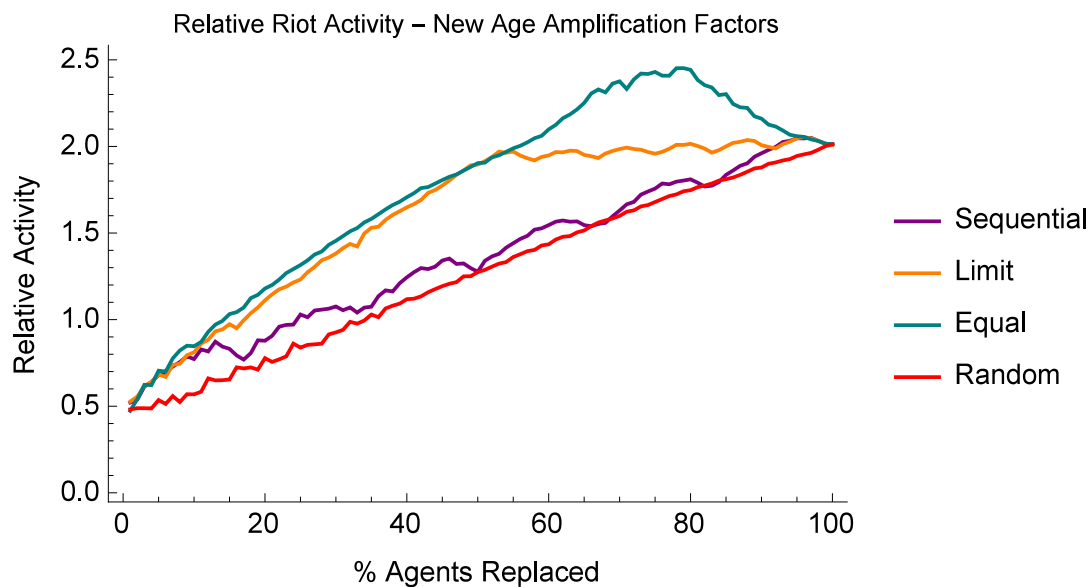
between the ages of 15 and 29 are amplified, and the hardship of other agents is dampened. An alternative approach is to base these factors on data from the London riots. By combining the arrest records presented in Table 2.2, and the age distribution of the London population [200], I obtain a new set of age-factors, which are shown in Figure 6.10. By dividing the relative frequency of each age group in the arrest records by the relative frequency of the age distribution for London, the result are the ratios to which certain ages are over or underrepresented in the arrest record compared to the whole population of London, which can be used as a set of alternative age-amplification factors. Figure 6.10 shows that these new amplification factors based on the data from the London 2011 riots are significantly higher than the factors I have used previously, including in Chapter 4. Conversely for the older part of the population my own estimates are much higher than what is represented in the data for the London riots.



**Figure 6.10: Age amplification factors based on data from the London riots [127, 200] and standard factors used in the model.** The hardship of agents is multiplied with an amplification factor based on the age of the agent (x-axis). The standard factors used in the model are shown in orange, and are the same as the age factors shown in Figures 6.6 and 3.1. An alternative to these would be to use data from the London riots. The age factors that are based on data are shown in blue, and are obtained by dividing the relative fraction of arrests per age group during the London riots [127] by the age distribution of London [200], resulting in the relative over- and underrepresentation for each age group in the number of arrested individuals.

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I re-evaluate the second experiment with the new age-amplification factors, in which I replace resident agents with the Stockholm age distribution by immigrant agents with the age distribution based on immigrants coming into Sweden. Figure 6.11 shows the effect the new age-amplification factors compared to the reference run (Figure 6.3) for the four main distribution mechanisms described in Section 6.3.3. The reason that I leave out the two different replacement algorithms is that local random replacement mechanism results in the same behaviour regardless of the global distribution mechanism, as shown in Figure 6.8, and therefore only using global random distribution suffices. For the other three distribution mechanisms (sequential, limit, and equal) shown in Figure 6.11 I use sequential replacement of agents along the ring lattice, in counter-clockwise direction.



**Figure 6.11: Effect of using age amplification factors based on data from the London riots on relative mean riot activity.** *Effect of using amplification factors based on data when replacing resident agents with immigrant agents, using Sequential (purple), Limit (orange), Equal (green), and Random (red) distribution mechanisms (see Section 6.3). In the first three mechanisms the agents are sequentially locally replaced, and the random distribution mechanism uses random replacement. The relative mean riot activity is shown on the y-axis, and the percentage of agents replaced on the x-axis. The mean riot activity is expressed relative to the reference model run (Figure 6.3).*

Without replacing the resident agents, the introduction of the new set of age-amplification factors causes a considerable drop in riot activity compared to the reference run (Figure 6.3). The riot activity drops to 50% as a result of the introduction of the new age profile, which is based on data from the London [127, 200]. In this

new set of amplification factors, only the grief of agents younger than 30 is amplified, whereas the hardship of older agents is dampened. The decrease in riot activity is caused by the lower amplification factors for older agents, which form a big part of the Stockholm age distribution (Figure 6.6). As the resident agents are replaced by immigrant agents, which are on average younger and have more than half of the population aged under 30 (see Figure 6.6), the riot activity increases. When all the resident agents are replaced, the riot activity is twice as high. The new age sensitivity therefore increases the riot activity by an additional 40-50% in the model when all agents are replaced (see Figure 6.8).

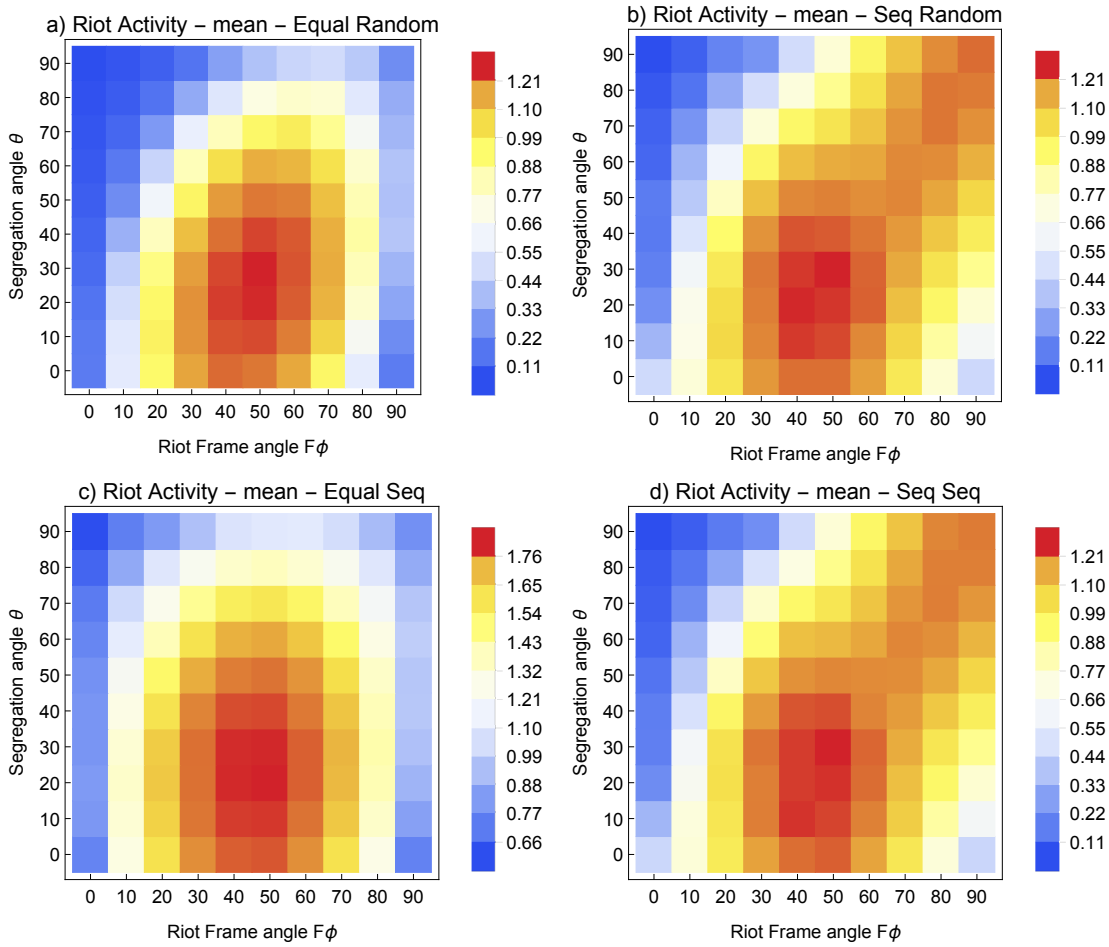
#### 6.4.4 Association and Coalitions through Riot Frames and Segregation of Hardship

One pathway through which immigrants can potentially exacerbate existing susceptibilities to unrest and violence is through association with existing problems, for example social exclusion of established minorities. If the immigrant agents are sympathetic to the riot frames proposed by the resident agents and their grievances overlap, the potential number of individuals that would participate in the riot grows, leading to more riot activity. To study under which conditions the immigrant agents would be prone to form such coalitions with the resident agents, I initialise the model with half of the resident agents replaced by immigrants (15,000). The hardship of the agents is described along two dimensions, that each represent a different and independent issue about which the agents can be aggrieved. I then vary the riot frame angle  $F_\phi$  and the segregation angle  $\theta$ . The riot frame  $F$  represents what the agents perceive the riot to be about, and is measured along the same two dimensions as the hardship of the agents. Because the magnitude of the riot frame vector is limited to 1, it can be described by its angle towards the x-axis, the riot frame angle  $F_\phi$ . The segregation angle  $\theta$  is the degree to which the grievances of the resident and immigrant agents overlap, and is described in greater detail in Section 6.3. As  $\theta$  increases from 0 to 90 degrees, both populations become more focused on the issues that uniquely relate to their own communities. At 45 degrees, there is no overlap in hardship, and at 90 degrees, the resident agents only care about issue X, and the immigrant agents only about issue Y.

Figure 6.12 shows the relative riot activity to the reference run under the influence of alternate riot frame and segregation angles, for different global distribution and local replacement mechanisms. Depending on the segregation angle, riot frame, and

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the way in which the resident agents are replaced, the riot activity increases 40% to 100%, but can also drop to levels where there is hardly any riot activity.



**Figure 6.12: Relative mean riot activity at different segregation and riot frame angles.** *Relative mean riot activity for different distribution and replacement mechanisms: a) Equal distribution, Random replacement, b) Sequential distribution, Random replacement, c) Equal distribution, Sequential replacement, and d) Sequential distribution, Sequential replacement, at different settings for the segregation angle  $\theta$  (y-axis) and riot frame angle  $F\phi$  (x-axis), measured in degrees. The distribution mechanisms describe how agents are divided over the riot locations, the replacement mechanisms describe how agents are locally replaced within those riot locations. Riot activity is expressed to the reference model run (no segregation, riot frame angle at 45 degrees).*

Figure 6.12 shows the same result as in Chapter 5 (Figure 5.8), despite different experiment setups; small levels of segregation of hardship increase riot activity. In Chapter 5, the segregation angle varies the overlap of agents in different riot locations, such that agents in one riot location are aggrieved about issue X, and agents in another location experience hardship over issue Y. In the experiment in this chapter, the

segregation angle also describes the overlap in hardship of two agent populations, but now they are mixed within the same locations. Chapter 5 focuses on the spread of riots from one location to another as the two agent groups are separated over two distinct locations, whereas in this chapter those communities are located within the same network cluster.

Dividing the immigrant agents equally over all riot locations, and replacing resident agents randomly within the network cluster, results in a maximum increase of 40% in riot activity (Figure 6.12a). Due to the increased riot propensity of the (younger) immigrant agents, the pattern is slightly asymmetrical, resulting in higher riot activity when the riot is more about the issues specific to the immigrant agents ( $F_\phi$  is higher than 45 degrees) at higher levels of segregation. When similarly dividing the immigrants equally over all clusters, but replacing them closer together in the riot location using sequential replacement (Figure 6.12c), the maximum riot activity becomes twice as high as the reference model run at small levels of segregation. The asymmetrical pattern from Figure 6.12a largely disappears, and riot activity is generally higher compared to the random replacement of immigrants.

Sequentially distributing immigrant agents over the riot clusters leads to a maximum increase in riot activity of 25%, regardless of the way in which the immigrant agents are placed within those riot locations (Figures 6.12c and d). The sequential distribution mechanism results in an increased asymmetrical diagonal pattern, where the riot activity remains around the same level as the reference run when the riot is about the issues relating to the immigrant agents, and these agents are also predominantly focused on these issues. Therefore without any coalition forming, the immigrant agents can sustain the similar riot levels with half of the agent population under these settings. The sequential distribution mechanism distributes replaces all of the resident agents in the first three clusters, including the cluster where the riots start. The immigrant agents therefore do not have to rely on the resident agents to gain enough riot participants to sustain longer riots and prevent such deterrence from the police response that the riot immediately stops.

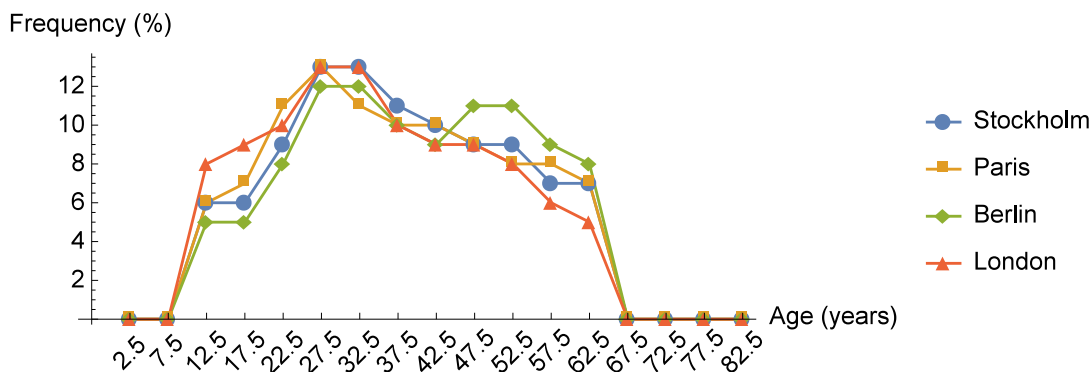
#### 6.4.5 Age Sensitivity and European Capital Cities

In this chapter I have framed the coalition formation between different groups and the effects of demographic shifts in terms of immigration, and have used the previous episodes of violence in Stockholm as the context to motivate and set up the



## 6.4 Results

experiments. Figures 6.1 and 6.2 show that the uptake of asylum applicants has also considerably increased in other member states of the European Union. To investigate the sensitivity to demographic shifts in the model for other major cities in Europe, I change the age distribution of the resident agents to the age distributions of these cities. In addition to Stockholm I use the age distributions of Paris, London, and Berlin, shown in Figure 6.13. The reason for choosing these cities is that Paris and London both experienced riot activity in the past decade (Paris in 2005 [171] and London in 2011 [48]), and Germany is currently accepting the most refugees out of any EU member state, three times the number of Stockholm (see Figure 6.2) [57, 58].



**Figure 6.13: Age distributions used in the model for Stockholm, Paris, Berlin, and London.** Based on data from the national offices for statistics [85, 181, 182, 200].

The age structure of the populations of Paris, Berlin, Stockholm, and London are relatively similar. Of all four capitals, London has the largest share of younger individuals, whereas Berlin has the oldest. I populate the model with resident agents, of which the ages are based on the age distribution within these four capital cities. I then replace the resident agents with immigrant agents, of which the age distribution is still based on the immigrants arriving in Sweden. I vary the number of immigrant agents that replace the resident agents, and compare the result to the the reference model run to obtain a relative mean riot activity. The immigrant agents are distributed in two different ways; 1) global limit distribution and sequential local replacement, and 2) random distribution and random replacement. These two options represent the two extremes in this chapter, as they cause the highest and the lowest intermediary riot activity as more immigrants are added (see Figure 6.8). The results are displayed in Table 6.2.

**Table 6.2: Mean riot activity predictions for Stockholm, Berlin, Paris, and London.** Resident agents are replaced with immigrant agents, causing a demographic shift and different levels of riot activity. The age distribution of the resident agents depends on the location (Figure 6.13). The mean riot activity is measured relative to the reference model run (Figure 6.3).

	Stockholm	Berlin	Paris	London
<b>Limit Distribution, Sequential Replacement</b>				
<b>% Agents Replaced</b>				
0	0.53	0.32	0.71	0.91
25	1.23	1.05	1.38	1.5
50	1.89	1.79	1.98	2.11
75	1.96	1.9	2	2.05
100	2.01	2.01	2.02	2.01
<b>Random Distribution, Random Replacement</b>				
<b>% Agents Replaced</b>				
0	0.48	0.25	0.64	0.88
25	0.84	0.62	0.98	1.13
50	1.27	1.15	1.35	1.44
75	1.68	1.63	1.71	1.75
100	2.01	2.01	2.01	2.01

Table 6.2 shows that of all the cities, the age distribution of Berlin results in the lowest riot activity without any replacement of the resident agents. The riot activity then is more than twice as low as in Paris and London, and nearly twice as low as Stockholm. These values are a reflection of the age structure of these cities. Despite the fact that Stockholm has had the highest frequency of conflict in the past decade, the relative riot activity is lower than Paris and London. Of all cities London has the highest propensity to civil unrest according to the model when none of the resident agents are replaced. As immigrant agents are added to the network, the differences between the cities start to dissipate. The random distribution mechanism always leads to lower riot activity, and the rise in activity as more agents are replaced is much more gradual compared to the other mechanism. If the global limit distribution in combination with the sequential replacement is used, the riot activity is much more sensitive to the initial replacement of resident agents, and becomes relatively insensitive after 75% of the population consists of immigrant agents.

## 6.5 Discussion

In this chapter I have proposed two pathways through which the current ‘immigration crisis’ in the EU could potentially increase the risk of violent civil unrest. The two pathways through which immigration can lead to an increased probability of unrest in the future are: 1) association with grievances of existing minorities that have caused unrest, forming coalitions and increasing the potential riot size, and 2) demographic shifts, leading to an overrepresentation of groups that are highly associated with conflict. The research questions that I addressed related to these pathways are: 1) How does the number and the distribution of potential rioters in cities influence riot activity, probability, and spread? 2) How does the distribution of different riot groups and overlap in hardship influence riot dynamics? 3) To what degree are riots more likely due to the current influx of migrants through association and demographic shifts?

I have explored these pathways and research questions through a general mechanistic agent-based model. Some of the experiments were set up in the context of asylum seekers arriving into Sweden, but the underlying methodology and consequently also the results are much more general and go beyond issues that merely relate to immigration. These experiments were only specific to certain locations through the age distribution of the resident and immigrant agent groups, and without these could be about any two (abstract) populations or communities. The experiments in this chapter complement those of Chapter 5. In Chapter 5 I also study the formation of coalitions between different communities under the influence of different riot frames and levels of segregation of interest, but the difference is that in Chapter 5, each riot location consists only of one of the two agent groups, whereas in this chapter the agent populations are mixed through the riot locations. Next to studying coalitions between two agent groups and collective participation in unrest I have also investigated how riots are formed and established as the number of rioters grows, and the effect of demographic shifts on riot activity.

The first result is that a random spatial distribution of potential rioters over different neighbourhoods in the model reduces the potential for riots. Conversely if rioters are more concentrated within the same neighbourhoods, and in addition form clusters within these locations, the potential riot activity and duration quickly increases as the number of potential rioters grows (Figure 6.7a). In the other two distribution mechanisms the riot activity remains very low up until 50% of the population is willing to participate. As the potential riot population grows beyond

this threshold, the riot activity rapidly increases (Figure 6.7b and c). The way in which potential rioters are displaced throughout urban environments and social networks could be one explanation for why a significant number of people might feel perpetually aggrieved about structural issues in society, but consequently does not lead to recurrent outbursts of conflict. The quick increase in riot activity in these distribution mechanisms can also help explain why some riots might come as a surprise, as the potential riot activity significantly increases in the model once more than 50% of the agents becomes willing to participate.

Another implication of the first experiment is that according to the model, unrest that solely relates to one issue can best be prevented by ensuring that no local concentration of potential rioters is formed. In the context of immigration, one way to achieve this would be to allocate asylum applicants housing in random locations. Additionally such an approach could also potentially help prevent local segregation, as it becomes necessary for immigrants to interact with their environment. However, minorities are rarely randomly dispersed throughout a city [150], and with time are likely to overcome such separation and scattering through for example online social media. Moreover studies of segregation have shown the existence of certain 'tipping points' or critical thresholds (e.g. [41, 169]), where if the diversity of an area increases beyond a certain point, all the native residents move away. Such a shift in a neighbourhood can propel the number of potential rioters beyond the threshold of 50% in the model, significantly increasing the potential riot activity.

In the second experiment I replaced resident agents by immigrant agents, which induced a demographic shift in the age structure of the total population. The only difference between the two agent populations were the underlying age distributions. Unlike the first experiment, both agent groups were willing to participate in the riot. The younger age structure of the immigrant agents could lead to increases in riot activity up to 60% compared to riots that only featured resident agents (Figure 6.8). The random local replacement mechanism caused the slowest increase and resulted in similar levels of riot activity for the same number of immigrant agents, regardless of how they were distributed over the different communities. This reinforces the implications from the result of the previous experiment, that random local dispersement of potential participants can help prevent violent outbursts. Conversely spreading out the immigrant agents globally over the communities, but allowing them to cluster locally results in the highest amount of riot activity, especially if only the elder resident agents were replaced. Even if only a small part of the resident population is replaced by immigrant agents, for example 20%, the riot activity

increases by 25% in the model.

The direction of replacement in the experiment has a big impact on riot activity in the model, as it dictates which age group in the resident agent population is replaced first. When young resident rioters are replaced first, the riot activity initially decreases as more agents are replaced, after which the riot activity sharply increases to 145% (Figure 6.9). As the ages of the immigrant ages are randomly drawn according to the age distribution of asylum seekers coming into Sweden [57, 58], young resident agents can be replaced by immigrant agents of all ages, which on average leads to the decrease in riot activity. This scenario however, where very young residents are replaced by immigrants, is less likely to occur in the real world than the counterpart, where immigrants take the place of elder residents.

In my model the hardship of the agents is convolved with an age sensitivity to boost the grievances of younger agents, and dampen those of older agents, accounting for patterns in the data that show that younger individuals are much more prone to engage in riots than their elders [45]. Up until this chapter I have used a ‘conservative’ estimate of the age sensitivity of agents, increasing the hardship of young adolescent agents by a maximum of 25%. An alternative approach is to use data from the London riots [127, 200], which shows a much higher sensitivity to age, up to a maximum of 300%. Implementing the new age amplification factors increased the sensitivity to the demographic composition in the model, resulting in more variance in the potential riot outcomes. The maximum riot activity increased by another 40% as a result of the demographic shift, adding up to a doubling in riot activity compared to the reference model run (Figure 6.11). However, this new age sensitivity also caused a drop in riot activity when none of the resident agents were replaced, lowering the mean total riot activity by 50%. This increased variance can help explain why there was such surprise over the 2013 Stockholm riots, as without any demographic shift the potential for riots is very low following the age distribution of the current Swedish population.

The new age sensitivity is only based on the London 2011 riots, and raises questions about generality, and consequently about applicability of this pattern from the London 2011 riots to Stockholm and other areas. Statistical research has demonstrated that there is a relationship between the age structure of a population and the incidence of conflict [45], but the individual propensities per age group have not been shown yet. To properly assess the generality of the age sensitivity based on data from London, more data would be necessary from other events, also to find if a general age sensitivity can even be established or whether this is individual to each

region.

One of the proposed pathways by which the potential unrest could increase as a result of immigration is association with riot frames that encapsulate both resident and immigrant populations. The result from Figure 6.12 is that similarly to Chapter 5; small differences in grievances between communities increase unrest if the riot involves both parties equally. This result is both for two different communities that are separated over physically different locations, as well as two communities that are mixed within the same neighbourhoods. Moreover Figures 6.12b and d also show that, under certain conditions, the immigrant agent population on their own can establish a riot of a similar size compared to the full population. The conditions under which the immigrant agents do not depend on the formation of a coalition, are that they are concentrated over a limited number of areas, they are prone to only be aggrieved about their own specific issues, and the riot frame is perceived to capture specifically these issues. This effect is caused by the age-amplification factors, and Figures 6.12b and d also show that without this effect and the formation of coalitions between the two groups, neither group can sustain a riot that is solely related to their own specific grievances.

Using the new age amplification factors, I change the age distribution of the resident population from Stockholm to other major capital cities in Europe, including London, Berlin, and Paris. For these three additional locations, I study the influence of demographic shifts on riot activity using two distinct distribution mechanisms for the immigrant agents. Table 6.2 reveals that despite Stockholm having had the highest frequency of conflict in the last decade [114, 170], it is not the most sensitive of the four. Aside from local differences in segregation and hardship, one reason that could explain why Stockholm has experienced more rioting is that over the years they have taken in relatively more immigrants per capita. In 2015 for example, the number of non-EU asylum applicants in Sweden was twice as high as that of France [57, 58] (see Figure 6.2), whereas the total population size of France is more than six times larger than that of Sweden (66 versus 10 million) [85, 181]. According to Table 6.2, London is the most sensitive, but the UK uptake of asylum seekers is even lower than that of France [57, 58]. Additionally the 'hidden' youth bulge might have played a role in Sweden. As discussed in the Introduction in this chapter, the main groups of immigrants in Sweden have a relative high frequency of young adolescents, that is not detected when analysing the whole population of Sweden. If these groups are clustered in the same neighbourhoods, the likeliness of conflict increases according to the model (Figure 6.8).

The influence of age structure of a population has not previously been explored within numerical models of civil violence. In this chapter I examined the sensitivity of riot activity to demographic shifts in the context of immigration, by using the age distribution of asylum applicants arriving in Sweden. The immigrant agents replaced resident agents, which had their age distribution based on different capital cities in Europe. Some of the results, like for example the 45% to 100% increase in total mean riot activity, occur when all the resident agents are replaced by immigrants, which are quite improbable scenarios. To get a better understanding of how the probability of riots changes as a result of demographic shifts, for in this case induced by immigration, the sensitivity of the model should be combined with migration projections (e.g. [13]). The main reason to include the effect of age in the model is that research has shown that certain groups are frequently associated with conflict (e.g. [45]). This effect however is dependent on underlying conditions such as perceptions or feelings of (group-based) disenfranchisement, which also has to be taken into account when making predictions about the possible influences of migration. Indeed other studies have shown that explicitly giving young people economic opportunities, for example summer jobs, reduces the potential for violence [78].

In this chapter I only focused on how riots are influenced through immigration by considering pathways in which the immigrants would participate in unrest. However, in multiple countries there have been protests, and in some cases also violence, against the arrival of asylum seekers (e.g. [76]). One particular striking example is the town Oranje (Orange) in the Netherlands, where the Dutch government attempted to place 1400 asylum seekers in a town that has 140 inhabitants [1], leading to outrage and unrest. Such demonstrations and protest are not included in the model, but their probability could potentially increase as well as a result of (mass) migration.

The message of this chapter is not that immigration is bad and should be stopped. The two pathways that I have explored impact the probability of riots only in a negative way, in the sense that more immigration leads to a higher probability of conflict through demographic shifts. This is not the only effect of immigration, and (more) immigration does not necessarily lead to outbursts of violence. The results about the effect of the community structure between different groups of rioters highlight that only certain situations, such as overlap in grievances and very strong local clustering, could potentially lead to (more) riot activity. In this chapter I have assumed that the incoming immigrant agents have feelings of hardship and reasons to riot, which might not necessarily be true in the real world. However, many of the

recent riots in the western world can be traced back to issues surrounding minorities and segregation (e.g. Stockholm 2013 and Baltimore 2015), and as such policy makers should be, perhaps increasingly, aware of the potential negative impacts shown in the results and the real-world equivalent circumstances in which they occur. The message of this chapter is therefore that in the context of the current immigration problems, it would be prudent to ensure that policies are in place that enable the currently arriving asylum applicants to fully integrate and participate into their new communities and countries, preventing the scenarios that I explored in the model.





# CHAPTER 7

## Discussion

**Author Contributions:** This chapter was written by Jelte Mense, with editorial contributions from Paul Palmer and Matthew Smith.

# 7.1 Introduction

Over the past few chapters I have studied how certain underlying conditions, such as the number of protests preceding a riot and the topology of the contact network between agents, influence the dynamics of riots, for example the duration and spread. In this final chapter I combine, summarise, and discuss the results in Sections 7.1.1 and 7.1.2. I further discuss the use of mathematical models for predicting riots in section 7.2, and consider specifically my own model in 7.3. The last section 7.4 highlights potential future directions for riot research that can further help enable the prevention of future civil conflict.

## 7.1.1 Research Questions and Summary

In this thesis I addressed the main research question: what the determining factors are that drive riot behaviour? ( $Q_0$ ). To answer this research question I developed and presented a new agent-based model of civil violence. To find the determining factors I split the main research question in three different parts:

Q<sub>1</sub>) What is the influence of pre-gatherings on riots?

Q<sub>2</sub>) How do network properties and (dis)similarities in collective identities between communities facilitate coalition formation and the spread of violence?

Q<sub>3</sub>) How are riot dynamics influenced by social, spatial, and demographic structure of potential riot populations?

By addressing the main research question in this way I have studied different aspects of events of civil violence. I have investigated the effects of events taking place prior to riots, the police response, and the accuracy of information in Chapter 4. The aim of Chapter 5 was to find out under which conditions, and with what probability, riots spread from one location to another. The main factors under investigation were 1) the network properties within and between different communities, 2) riot frames that describe what the riots are about, 3) segregation between communities (collective identities and grievances), and 4) the relationship between multiple issues about which individuals may be aggrieved. Lastly in Chapter 6 I investigated the effects of segregation and composition within, rather than between, communities. Additionally I used the age distributions of multiple European capitals to assess the sensitivity to potential future unrest in these cities.

In Chapter 4 I applied the model to a specific event, the London 2011 riots, whereas in Chapter 5 I generalised the model behaviour to simultaneously model multiple interconnected riot locations. In Chapter 6 I combined these approaches to discover the degree to which potential future riots are more likely as a result of the current immigration wave following the 2011 Arab spring.

### 7.1.2 Results

The main dynamics of riots that I have studied are the probability of a riot occurring, the total riot activity, and the duration. I expressed the riot probability as the probability of a riot occurring with a certain severity, measured in the number of days (e.g. the probability of a 5-day riot). The riot duration is measured as the difference between the start and end time of the unrest in the model. Lastly the total riot activity is the sum of the number of participants over the whole riot duration. Aside from these three main riot properties, I developed several other metrics to capture the behaviour of riots in the model, described in section 3.10.

The results from Chapter 4 show the influence of protests that take place prior to riots, initial police presence, and the accuracy of information for the police response in the model. The number of times that a protest is held before a riot (frequency) generates more riot activity than just the size of a protest. More police at the start of the riot helps contain the unrest more quickly. Inaccuracy and bias in the information that the police uses to inform their response to the riots can be mitigated by frequent updates of information, which also reduces uncertainty.

Chapter 4 is a demonstration about how the model can be applied to reproduce and study the dynamics of a real event, the London 2011 riots. By running multiple scenarios with different initial police numbers I investigate how the riots could have unfolded differently. The finding that more police could have helped contain the riots confirms that such events are sensitive to police response, although a perceived overresponse can also have counterproductive effects. These results could potentially help anticipate and contain future unrest more quickly.

In Chapter 5 I used the model to investigate when riots spread from one location to another. I found that there is a minimum number of connections between two communities necessary to facilitate the transmission of violence. Additionally I found that small levels of segregation in hardship between communities, representing

differences in interest and causes of grievances, increase riot activity and the chances of unrest spreading. Complex patterns of spread can be reduced to two primary patterns, where violence either spreads directly from one location to another or through a secondary passive location. Lastly I identified the conditions under which this pattern occurs, and riots spread through another intermediary community without violence occurring in that location. Such a community only passively facilitates spread when there is sufficient interconnectivity to other locations, enough difference in interest between the riot locations, and the riot frame does not apply locally.

The speed by which violence spread in the London 2011 riots and the Arab Spring that same year are believed to be related to the rise of online social media. The results from Chapter 5 are therefore particularly current, due to the widespread adoption of mobile phones which grant perpetual access to social media. Online social media has created denser communication networks, increased the frequency with which individuals communicate, and expanded the opportunities to share information more quickly. This allows individuals to self-organise more easily, mobilising more individuals within a shorter time and over further distances, facilitating the formation of coalitions and coordination between multiple communities and potential riot locations, promoting the spread of riots. Police forces, such as the MPS, will have to adapt to these new communication mechanisms to form an appropriate police response. In particular the response to the London 2011 riots is considered by some academics to have been amateurish [6], as they were unable to contain the riots. Moreover one of the lead authors on the 'Reading the riots' from LSE claims that the conditions that caused the London riots are worse now than five years ago [112, 217], such that unrest in London might soon recur.

Lastly the results presented in Chapter 6 highlights strategies which help mitigate potential future conflict involving multiple groups with separate grievances, for example resident established and newly arrived immigrant minorities. I also list the sensitivity of different European capitals to such events by assessing the influence of the age distribution in the model. The first result is that potential riot coalitions between different groups can be best prevented by allocating incoming immigrants in the model housing in random locations, rather than placing them in neighbourhoods that already have a high concentration of members of the same group. Moreover I also found that small levels of segregation between groups living in the same area increase the potential riot activity. Replacing elder residents by young adolescent immigrants can result in longer and more intense riots. Although Sweden is not the most

likely to experience civil unrest of all the investigated European capitals, the higher immigration per capita than any of the other countries that were investigated can help explain why it has experienced riots most frequently in the last decade, especially when combined with 'hidden' youth bulges that are only present in minority groups.

To obtain these results I combined the approach of Chapters 4 and 5, by focusing on real world locations such as in Chapter 4, but coupling riot locations by representing them as interconnected network clusters of the inhabitants of these locations as introduced in Chapter 5. I have demonstrated how the model can be used to reproduce the main dynamics of past events, as well as how the model can be used to understand how the occurrence of conflict might change in the future. Combining the results of the three chapters, I have addressed a wide variety of important factors that drive riot dynamics. These factors range from properties of individuals, such as their hardship, to events that fall into other categories of civil unrest, such as protests preceding a riot. There is no single factor that solely causes riots, all factors have interdependent effects on each other, and consequently form the probability of conflict together.

# 7.2 Riots and Mathematical Models

To answer the research questions posed in this thesis I have developed and described a new agent-based model of riots. I have used the model to investigate what drives riot behaviour and outcomes. The study of protests and riots accelerated after the race riots in the USA in the 1960s. The quick succession of multiple events in a relatively short time in a single country led to a relatively high availability of data, enabling quantitative analyses. This resulted into the discovery that the only two statistical predictors of violence were the non-white population size and whether a city was located in the southern part of the USA [178, 179, 180].

Statistical analyses can help detect relationships between variables. More recently researchers have also used statistical models to study and explain the diffusion of violence in these race riots [131, 132]. One way in which mathematical models in general are useful for studying complex systems is by identifying and isolating the main processes that are thought to drive behaviour to forecast how such systems might behave under different circumstances. Additionally in the context of civil violence mathematical models can be used as an alternative to real-world experiments, which would be likely unethical and generally unfeasible [48]. Moreover events of civil unrest are generally regarded as undesirable, and collecting high resolution data, like tracking individuals, is hampered by the chaotic and violent nature of the interactions between masses of rioters and police. Lastly the outcomes of mathematical models can be used to create and inform evidence-based policies [48], for example on police responses to civil unrest.

Mathematical models can be particularly useful for experimenting with police responses. Police forces already use real-world simulations to train staff and practice response to riots (e.g. [154, 166]). Using a mathematical model in addition to real-world simulations of events can help extrapolate and upscale experimental approaches to a larger area, that might be unfeasible to simulate in real life. Moreover such real-world simulations are time consuming and potentially expensive, whereas numerical models can be ran in the background. Numerical models have already been used to study optimal responses to crime (e.g. [220]), and can similarly be used to help contain riots.

The model that I described is designed to be a mechanistic model, where the focus is on capturing and describing the processes underlying the system that is under

investigation. In my agent-based model the processes are simplified and stylized versions of observations from the real world, that together establish a causal link in the model between initial conditions and model behaviour. In statistical models input variables are similarly transformed into output variables, with the key distinction that the involved calculations are not based on these underlying processes and the causal links between them. Instead, these calculations are designed to, for example, minimise error between model prediction and observations, and study which input variables best explain the patterns in the data.

Statistical analyses are now commonplace in the academic disciplines of social theory to both support and invalidate proposed hypotheses. For example the SIMCA model proposed by van Zomeren et al. is a meta-study and re-analysis of more than 180 different studies, all employing statistical methods to support hypotheses about what drives protest participation [221]. Causal or ‘mechanistic’ models can complement these methods by inverting the process; the mechanisms proposed by social theorists can be implemented into numerical models, such that these models can demonstrate if and how hypothesized relationships between variables result in observed behaviour.

The study of civil violence involves a wide variety of academic disciplines (e.g. [142, 143, 184]), but an even more inclusive and interdisciplinary approach might help better understand how these events start and evolve afterwards. Despite 50 years of research from social theorists, violent outbreaks still continue to occur and surprise [20, 121]. Mathematical models could help in creating more understanding about events of civil violence, but not without taking into account the large body of existing literature on why these events happen, as I have done in this thesis. Many of the current models of riots are based on Epstein’s work (e.g. [129, 198]), which disregards half a century of research on why riots occur. A more holistic approach towards modelling of civil violence, by increasingly including the main theories contributed by different disciplines of social theory, will more likely enable the prediction of civil violence than isolated research.

Moreover the concurrent, and sometimes isolated, research of different disciplines studying the same phenomena can lead to duplication efforts. This is not necessarily a problem, as using different methods to confirm the same findings can make results more robust. Without communication across different disciplines however, conflicting results are potentially left undetected and consequently unresolved, further stressing the necessity to cross-reference between disciplines. In



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this thesis I have specifically integrated sociopsychological theories about protest and movement participation, along with sociological theories about collective action and critical mass. This is only a small selection of the efforts that have been made to understand these events. Within and outside the academic disciplines that I included in this thesis there are other bodies of literature that can be incorporated in numerical models and iteratively build towards a more inclusive approach of understanding these events.

## 7.3 A New Riot Model

There are several aspects of my model that have not previously been described in other models of riots. Additionally there are other concepts that have been proposed before, but have been used in an alternative and original fashion in my model. In this section I discuss my model of riots and highlight the most important and new contributions.

The first new component is the influence of pre-riot protests on riot behaviour. Theories of social psychology propose that collective identities are mutable, and can be formed as much prior as during to the emergence of movements [155], and thus also during protests that precede a riot. Moreover many events of civil unrest are preceded by protests or demonstrations, and in some cases evolve directly from such gatherings. Protests can therefore influence riot dynamics, as I demonstrate using my model in Chapter 4.

For the decision of the agents to join the riot, I have split the concept of hardship into different dimensions, representing different reasons for which the agents can be aggrieved. Previous studies have only described hardship using a single dimension. This relatively simple shift also allowed me to include ‘riot frames’, that describe what the agents perceive the riot to be about. The overlap between the agent hardship and the riot frame then becomes the primary motivator of the agents to join the riot. The concept of riot frames comes from social theory, that found that such frames are often built upon existing collective identities [155, 221]. The combination of multiple dimensions of agent hardship and riot frames enabled me to study under which conditions communities with different grievances form coalitions, and when violence spreads between different locations. Additionally I have used these novel methods to research the effects of segregation, and investigate the influence of relationships between different issues that foster riot participation.

The other components that influence the decision of the agents to join, the external motivation and the repression, are examples of concepts that have also been used in other studies, but have different implementations. In Epstein’s model for example the agents consider the probability of arrest when joining the riot, which is similar to the repression but uses a different combination of the number of active rioters and nearby police officers.

The concepts of agent fatigue and cooldown are two other concepts that have not

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been previously described in numerical models of riots. In other models agents can sustain riot activity indefinitely in the absence of police presence (e.g. [55, 129, 198]), leading to unrealistic behaviour. This is prevented in my model by the fatigue, which forces the agents to leave the riot over time. The cooldown additionally prevents agents from immediately rejoining the riots after they leave, which helps generating the observed daily cycles in riot activity as observed in the data from the London and Stockholm riots (see Chapter 2).

Previous agent-based model of civil violence have used a fixed number of police officers (e.g. [48, 55, 129, 198]), whereas I have described two different police responses with a variable number of active police officers. In Chapter 4 I used a sine wave to force a daily cycle to best capture the data from the 2011 London riots. In Chapters 5 and 6 I used a different method where the cycle in the number of active police officers is dependent on the riot activity.

### 7.3.1 Space and Arrests

Some riots take place in one location, whereas in other events of civil unrest violence spreads from one location to another. Such diffusion of violence has been extensively been studied for both the 2011 London riots [16, 17, 18] and the race riots in the USA [131, 132]. Different models of riots have taken distinct approaches to tackling diffusion of violence in models.

In my model I did not explicitly describe physical space in which the agents can move around. Instead potential riot locations are either modelled independently, such as in Chapter 4, or represented as coupled clusters of agents in a social network in Chapters 5 and 6. Based on observations from the MPS in the unrest in London in 2011, riots often take place around public places such as squares (see Chapter 2), combined with evidence that people are far more likely to participate in riots close to their home [18], I chose to model potential riot locations without considering physical distance. Distance is implemented implicitly in the model, as agents are limited to only join one of the riot locations and violence can spread between the agent communities.

Other models of riots let agents move around randomly on a grid or torus (e.g. [55]), or alternatively with targeted movement towards or away from police (e.g. [198]), or also model riot locations independently of each other (e.g. [48]). One thing to consider when modelling riots in space that has not been implemented yet is the local

geography and geometry, such as the layout of streets and buildings. This becomes particularly important when modelling the dynamics of the interactions between police and rioters, as narrow streets and large open squares will require different arrest tactics.

Next to physical space I also did not implement arrests in my model, as I could not find a description of arrest that satisfactorily matched the data on the 2011 London riots. Additionally I also found that Epstein's proposition of the probability of arrest in his model also did not capture those dynamics. The effects and effectiveness of arrests have been thoroughly examined and demonstrated by Siegel, who showed that the efficacy of repression critically depends on the underlying network structure [173, 174], therefore reducing the need to include it in my model.

### 7.3.2 Generality, Specificity, and Calibration

Some of the models that describe riots are specifically designed to explain the dynamics of a single event (e.g. [48]), while others target general dynamics of riots that are not exclusively associated with one riot (e.g. [55]). In this thesis I presented a new agent-based model of riots, based on different social theories about why such events occur. These theories, such as the sociopsychological theory of protest, are general in the sense that they apply to a wide variety of events. Similarly the model that I described is general, in the sense that the motivation of the agents is not specifically tied to a single event, and in theory can be applied to any riot event.

In Chapter 4 I applied the model to the 2011 London riots, and demonstrated how the model captures the main dynamics of the unrest in three boroughs in London. To showcase the generality of the model I would have liked to compare model output with more events, for example the 2013 Stockholm riots. Unfortunately the data that I received on that event was unsuitable to capture using this model. Good data on the dynamics of riots, such as the number of rioters and the number of active police officers, is not generally publicly available for events of civil violence. Showing how numerical models can be used to study riots might help persuade police departments to release more data on such events, which would in turn help improve these models and enable better future prediction of riots.

To capture the dynamics of the 2011 London riots using the model I had to 'calibrate' the parameters, i.e. set the parameter values such that the model behaviour

matched observations from the data. My approach was to first declare sensible ranges for the majority of the parameters. The fatigue and cooldown of the agents for example describe physical properties of the agents, and therefore have a limited set of possible values. The second step consisted of manually setting and varying parameter values to match the model predictions with the data. An alternative approach would have been to use a tool like Filzbach, developed by Microsoft Research, which wraps around the model and iteratively estimates parameter values using Bayesian inference [125]. This approach would have been particularly useful to generate parameter settings for all London boroughs, but was not worth the effort for the limited number of locations under investigation in this thesis.

### 7.3.3 Future Directions of the Model

In this thesis I have shown the influence of multiple variables on model behaviour. For example in Chapter 4 I examined the effect of the accuracy of information and initial police presence, and in Chapter 5 I vary the parameters of the network, and alter the differences between two communities to investigate when riots spread. I have shown how a relatively simple model can capture the complex dynamics of a real event. Instead of suggesting more concepts (.e.g from social theory) that should be added to the model and consequently increase the complexity of the model, I highlight small potential changes to the existing framework that could potentially lead to interesting results that advance understanding about riot behaviour.

#### 7.3.3.1 Riot Frame

One interesting property to add to the model would be to allow the riot frame to evolve or change over time. In the setup that I used in my research I have described the riot frame angle  $F_\phi$  as a fixed variable. In some riots however, the perception of what the movement was about has changed over time. For example the Occupy Movement started as a protest against 'Wall street' [40], but over time became a movement with a wider frame for protest as it spread globally.

To simulate such a change in the perception of what the unrest is about the riot frame angle could be allowed to change accordingly over time. One very simple way to do this would be to describe the riot frame as the (normalised) average hardship of the current participants of the riot. This method could potentially help explain why riots stop, as the most persistent and aggrieved groups of agents have a continuous

share in declaring what the riot is about. This could lead to a riot frame that is perceived by the other agents as too radical and extreme, stopping them from further participating in the unrest.

#### 7.3.3.2 Agent Knowledge and Messages

In the core model that I described the agents cannot join until they are contacted by other agents and receive information about the riot. The information about the riot transmitted to the agents is binary; the agents know that there is a riot in progress, or they do not. All other information about the riot is global; once an agent knows that an event is in progress that agent automatically knows the size and the number of present police officers during each iteration that agent considers participating. The messages that the agents pass to each other in the model can be expanded to also include more information about the riot, such as the size and the police presence.

The speed of transmission and location in the network then become more important, as outdated information on the number of police officers can potentially be dangerous. Agents underestimating the number of police officers or overestimating the riot size due to outdated information consequently are at a higher risk of being arrested. Similarly the model can then also be used to study the abuse of 'misinformation', where false rumours about the riot or movement size are purposefully spread to give potential participants a false sense of security in order to persuade them to join.

#### 7.3.4 The Shape of Hardship and Grief

The agent-based models of riots all feature a variable or value associated with the agents that describe their primary motivator to engage in riots. Epstein has referred to this in his model as 'hardship' or 'grief' [55], and has implemented it in his model as a random uniform distribution ( $U(0,1)$ ). Other models that are based on Epstein's work consequently follow his example and also implement grief as a uniform distribution (e.g. [198]). Similarly in my model I have also used a uniform distribution to describe the grief of agents, mainly to be able to compare the model behaviour and results to other models, and secondly in the absence of other information.

Other studies, some of which are also based on Epstein's work, have used other distributions to describe the grief of agents, but are fewer in numbers. Other

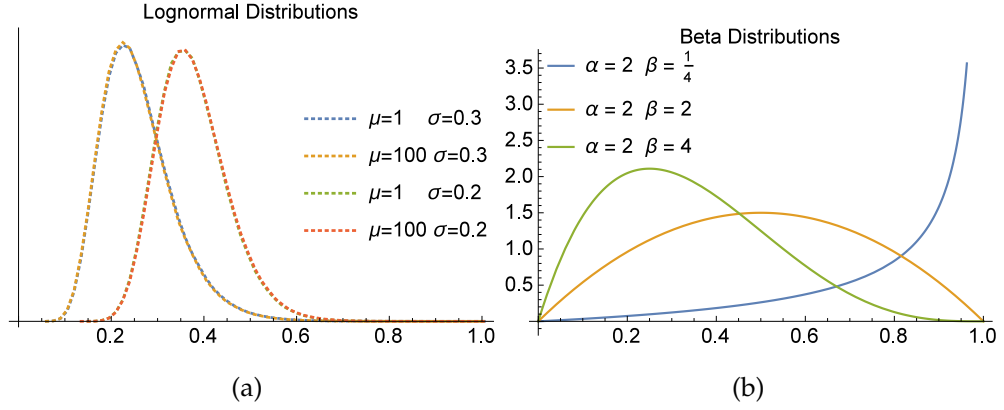
### 7.3 A New Riot Model

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distributions that has been used are for example, a logistic transformation of a lognormal distribution [129], and a chi-squared distribution [90]. The only study that I am aware of that uses data to describe the grief of agents is the Davies model of the 2011 London riots [48]. The authors in that study assign the grief of agents according to the UK Index of Multiple Deprivation [48]. Moro similarly uses monetary income as a measure for grief, and uses the lognormal distribution to assign income to agents [129]. The logistic transformation is then used to map the lognormal back to the interval between 0 and 1. According to Moro, this transformation indexes the difference between the agents income and the expected income in the population, and agent hardship becomes a decreasing function with income as a result. There is no justification given for using the chi-squared distribution [90].

The use of different distributions, across different and within the same type of models, leads to the question of what the ‘right’ distribution is that should be used to best describe the variation in emotions and grievances. Moreover because I used multiple dimensions of grief, I can segregate and polarise populations along these dimensions. At least 9 different types of polarisation between groups have been identified [32], and it would be interesting to see the effects of these in the model. But the use of the uniform random distribution to describe hardship is potentially a too strong simplification for one of the most important components of these models, the motivation of the agents to participate. A problem with using the uniform distribution is that each group is equally represented: there are as many disinterested as radicalised agents in the population, which might not be true. Moreover the use of the uniform distribution creates an underlying assumption that in absence of all other factors, on average half of the population would participate in events of civil violence.

Alternative candidate distributions that could be used in future agent-based models of riots are the lognormal and the beta distribution. As shown in Figure 7.1, these distributions have an off centre hump to the left, and a long tail to the right. This would describe a potentially more realistic situation in which the majority of the population have weak to medium feelings of dissent, and those who would join regardless of the circumstances are in the minority. A lognormal distribution was used by Moro to describe the differences in income between agents, but was transformed into hardship by passing it through a logistic function [129]. However, the given underlying reasoning is that the logistic transformation maps the income distribution (lognormal distribution) back to a number between 0 and 1, and that agents hardship is produced as a function of its relative position along the income distribution. Whereas in my model the agents represent potential rioters, using this



**Figure 7.1: Examples of Lognormal and Beta distributions.** *a) shows four examples of a lognormal distribution, b) shows three examples of a beta distribution, at different parameter settings. Both distributions can produce shapes in which there is an off centre hump, with a long tail to the right. The lognormal distributions in panel a) are mapped onto the interval between 0 and 1 by dividing the distribution by the largest sample in the set.*

transform even the richest agents are assigned a (very small) positive grief. Moreover it has repeatedly been shown that deprivation, and therefore also income, are very bad predictors for participation in such movements [92, 178, 179, 180, 184, 221]. Lastly the lognormal distribution can also simply be mapped to a number between 0 and 1 by dividing by the largest set in the sample, rather than by applying a logistic transformation.

Neither the lognormal and the beta distribution are optimal candidates. The range on the x-axis of the lognormal distribution exceeds the the interval of 0 and 1, and thus needs to be scaled back to this interval in order to be used to describe the hardship of agents. This reduces the flexibility of the distribution because it eliminates the mean parameter  $\mu$  of the distributions, as shown in Figure 7.1a. Despite significantly different parameter values for  $\mu$ , distributions with similar parameter values for  $\sigma$  perfectly overlap. The beta distribution does not have to be scaled back to the interval between 0 and 1, and describes a very wide range of shapes as shown in Figure 7.1b. Only a subset of these shapes describes the off-centre hump with a long tail, and the other shapes might not reflect real world situations.



### 7.3.5 One Ring to Rule Them All: Towards a Unified Model of Civil Violence

This work describes a model in which the motivations of the agents is based on general concepts such that theoretically it could apply to multiple riot situations. The differences in behaviour can then be explained from different parameter settings in the model, rather than having to compare different models for each specific riot situation. This work is a first step towards creating a model that can be used to describe a variety of situations.

In social theory new concepts and theories are integrated into the existing body of literature to create a 'unified' model of civil conflict (e.g. [115, 221]), and there are similar attempts for armed conflict (e.g. [172]). Advancing the work described in this thesis, or another model, to a stage where a single model can exhibit the dynamics of many events could be the numerical representation of such a unified model. Moreover such a numerical model has the opportunity to integrate and unify the body of literature from different disciplines, e.g. by merging resource mobilisation theory and the sociopsychological theory of protest.

Such a unified general numerical model of civil conflict could be used to increase understanding of the circumstances in which people riot, and potentially help detect those circumstances before events happen and enable prediction. Being able to identify when and where violent outbreaks might occur is not always desirable. In the Western world there are legitimate alternatives to the use of violence through freedom of press and speech. However in closed authoritarian regimes such as dictatorships, such a model could help those governments in repressing their populations and impede progress of social movements to obtain freedom. In some cases civil violence is a 'natural' way to create freedom for populations [215], and abusing predictions to limit and oppress could put countries in a perpetual state of potential conflict. This therefore raises the question for researchers what focus future studies like this should take, and exactly how real the predictions of these models should get.

## 7.4 Future Research

Next to the concepts that could be added or modified to my model, there are other methods to use and aspects of riots that are not included in my model but nonetheless could help understand how riots are initiated, progress, and end. In this section I highlight potential research directions which were considered during the course of this work

### 7.4.0.1 Riot Patterns

From investigating multiple riots, I observe that some countries experience several episodes of civil violence in quick succession. For example the first revolution in Egypt in 2011 was quickly followed by a second one [7], the current waves unrest in the USA in the past couple of years (Baltimore, Ferguson) [189, 190], and the instances of violence in Sweden [114, 170]. The same observations is also made by social theorists, such as Wilkinson: "We also know that the frequency and magnitude of riots at any given time is one of the most robust predictors of violence and political polarization at a later time" [215]. One way in which this can be modelled are self-exciting point processes, where past occurrences of an event make future events more likely. Such processes have been used to model natural processes like the aftershocks from earthquakes, but have also been used to model urban crime [128], and civilian deaths in Iraq [106]. Such techniques could potentially be used to find explanations why sometimes different events follow each other so quickly, for example it could be that during these events the use of violence was perceived as effective, lowering the threshold for future unrest.

### 7.4.0.2 A single spark can start a prairie fire; but only if it does not rain.

The main focus in this work has been to investigate what factors drive riot behaviour. In the model the main driver of the agents to join riots is the hardship or emotions relating to hardships. Individuals stop rioting in the model due to the increased effort of the police to repress the riots, not because their feelings are in any way diminished. This leads to the question of why riots in the real world end, and why they do not occur more often if grievances related to structural disadvantages are relatively constant [92, 184].

One reason amongst many cited by newspapers for why the London 2011 riots stopped was bad weather [194, 205]. Rain would have convinced people to

## 7.4 Future Research

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stay indoors rather than to continue the violence. Conversely newspapers are also suggesting relationships between warm weather and the occurrence of conflict [34, 39, 89]. Links between weather and crime [46], domestic and general violence [4, 124] and the 1789 revolution have been investigated [134, 135], but empirical evidence for a relation between rioting and weather has not been shown yet.

### 7.4.0.3 Climate Change and Riots

The original goal of this project was to understand how climate change would influence conflict, for example through a local shortage of essential resources, such as food and water. Under extreme circumstances individuals would likely engage each other in conflict over the ownership or access to these resources. The underlying reasoning for focussing on riots was that in situations where a considerable part of a national population would be deprived of essential resources under the threat of climate change, they would riot against the government to demand and enforce change. I found that there was no readily available quantitative model of riots that was able to describe multiple riot situations, so the focus shifted to developing a model that was general in nature, but could be used to describe real world specific events. Once established, such a model could then be used to study how climate change would impact riot probabilities across the globe. The last research Chapter 6 relates to this effort, as some have argued that the current displacement of a considerable part of the Syrian population and the Arab Spring were induced by climate change [69, 88].

After disagreements about the effects of climate change on conflict, the consensus is that climate change, in particular global warming, is positively related to the general occurrence of conflict [38, 81, 82, 168]. Climate change will therefore also change the probability of riots, for example through an increase in food prices [100]. The major challenge to understand these effects lies in predicting how humans will adapt to climate change [147, 177], as such major feedbacks between human influence and the climate can no longer be ignored. In this work I have contributed to this effort, by creating a model that can be used to study how climate change will effect the probability of rioting in the future.

# CHAPTER 8

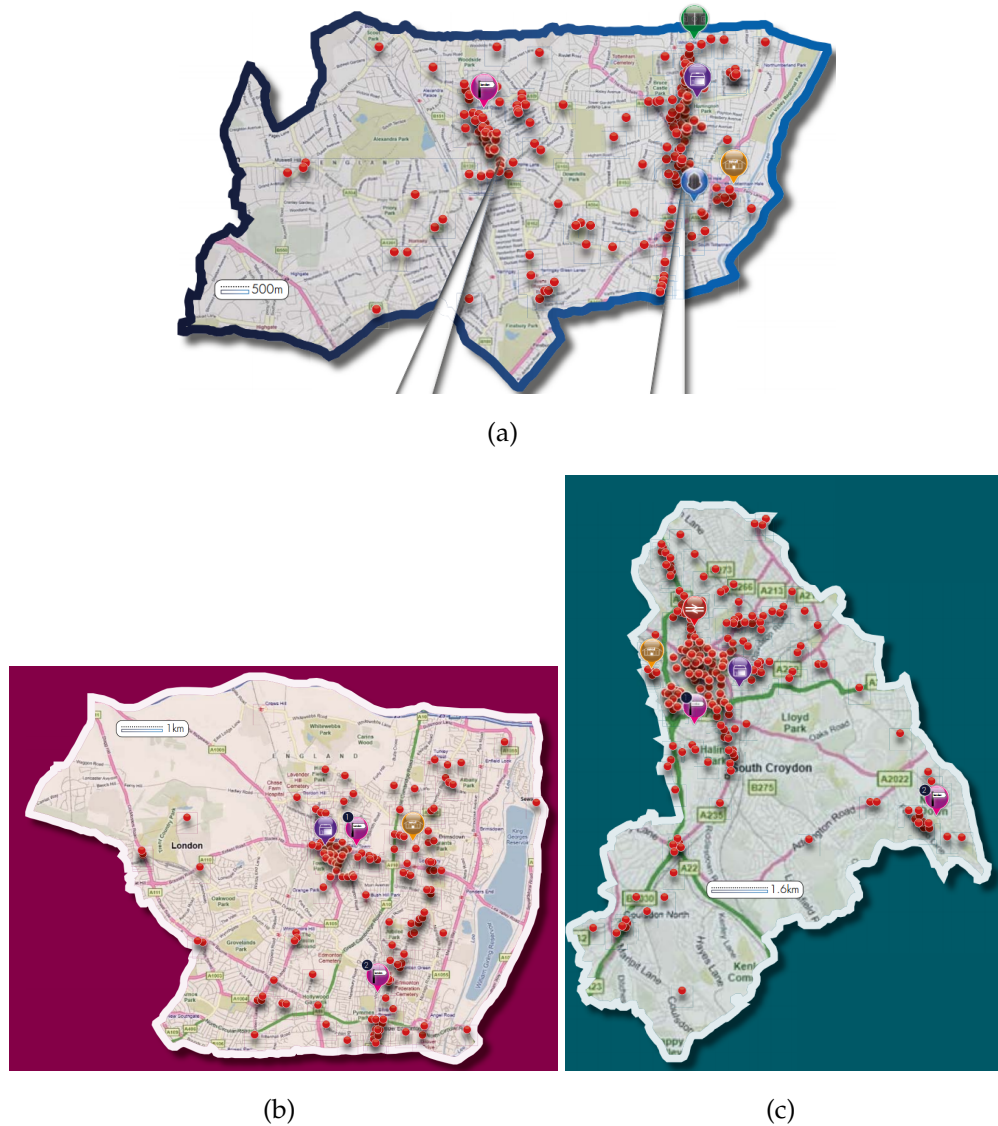
## Appendices

## 8.1 Appendix A



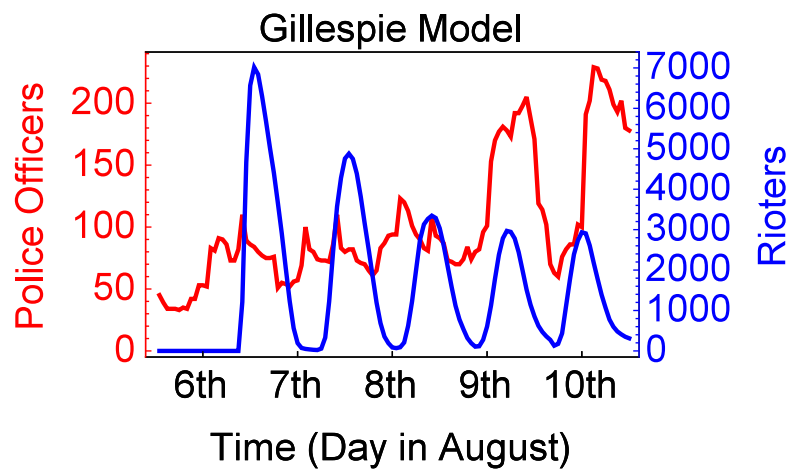
**Figure 8.1: Map of London boroughs.** *The boroughs modelled in Chapter 4 are Haringey (center-top), Enfield (center-top), and Croydon (center-bottom). Map taken from [109].*

## 8.2 Appendix B



**Figure 8.2: Map of incidents during the London riots.** Map of unrest in a) Haringey (top), b) Enfield (bottom left), and c) Croydon (bottom right). The maps show that incidents are clustered around certain areas. The red dots indicate registered disorder related incidents. The other symbols indicate several key locations within the boroughs, such as railway stations (red), police stations (blue), sports locations (green), and retail centres (yellow), borough centres (magenta), and further specific locations mentioned in the MPS report (purple) [121]. Taken from [121].

## 8.3 Appendix C



**Figure 8.3: Riot model using Gillespie algorithm.** *The number of rioters in the model is shown in blue on the right y-axis. The police response is replaced by the data from the London riots [122], shown as the number of active police officers in red on the left y-axis. Driving the model with the Gillespie algorithm and the police data produces similar results as using fixed time-steps and synchronised updating.*

## 8.4 Appendix D

Before arriving at the agent-based model described in chapter 3, I used differential equations to start modelling outbreaks of unrest. The main reason to stop developing a model using differential equations was that agent-based modelling allowed for easier integration of the theories from social psychology, especially on the individual level of the agents. Moreover informing the police response with the number of rioters of the previous day for example, would require the use of delay differential equations which are considerably harder to solve analytically.

Similar to the main model in this thesis there are two main components in the early prototype: the rioters and the police response. The police response  $P$  is defined as a number between 0 and 1. The population is divided into two groups: passive citizens  $C$  and active rioters  $R$ . I describe the fractional parts of the population that are passive and active, such that  $R + C = 1$ . As the total size of the population remains constant, I define two flows that represent the transition of passive citizens into active rioters  $\vec{CR}$ , and rioters becoming passive citizens  $\vec{RC}$ :

$$\vec{CR} = 0.1 \cdot \delta(t - 0.01) + C \cdot R, \quad (8.1)$$

$$\vec{RC} = 1.5 \cdot R \cdot P. \quad (8.2)$$

The flow from the number of passive citizens to active rioters  $\vec{CR}$  is dependent on the size of the riot population  $R$ . The larger the riot, the more attractive it is to join for the rest of the population. The growth of the riot size is bound by the remaining part of the population that is not in the riot  $C$ , to prevent overshooting. I start the riot by externally forcing a spike in the riot activity at  $t = 0.01$  through the Dirac delta function  $\delta$ , causing 10% of the of the passive population  $C$  to transition into  $R$ .  $C_0$  is initialised as 1, but to make the equation correct the  $\delta$  function should have been multiplied by  $C$ . I used this to be able to start the riot activity at any given time, but an alternative and more simpler method would have been to initialise  $R_0$  at 0.1 and  $C_0$  as 0.9, or any other desired combination that adds up to 1.

The decrease in the riot size is dependent on the police response  $P$ . As the number of police officers is often smaller than the actual riot size but is still able to stop the



riot, I multiply the police size by a fixed factor of 1.5, similar to deterrence in the main model. The decrease in the riot size is bound by the remaining riot population  $R$ .

Adding the in- and outflows for the two fractional populations  $R$  and  $C$ , the full differential equations are described below. The police response is dependent on the riot activity. If there is any riot activity, the police response increases to a maximum of 0.8. If the riot activity stops,  $P$  declines to 0.2.

$$\frac{dR}{dt} = \vec{C}\vec{R} - \vec{R}\vec{C} \quad (8.3)$$

$$\frac{dC}{dt} = \vec{R}\vec{C} - \vec{C}\vec{R} \quad (8.4)$$

$$\frac{dP}{dt} = \text{If } R > 0 \rightarrow R \cdot (0.8 - P), \text{ Else } \rightarrow -P + 0.2 \quad (8.5)$$

A numerical simulation for this system is shown in Figure 8.4, with initial conditions for  $R$ ,  $C$ , and  $P$ :

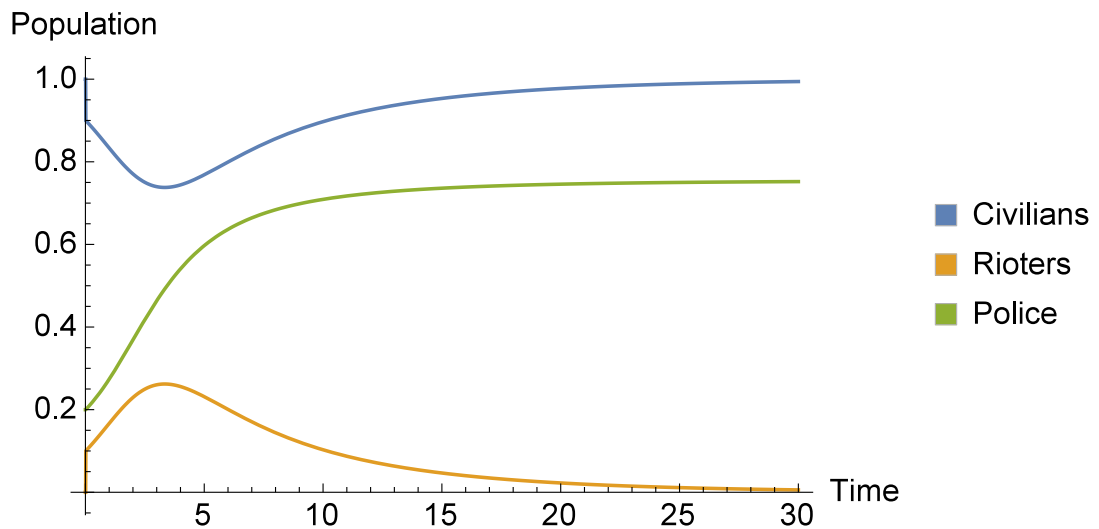
$$R_0 = 0 \quad (8.6)$$

$$C_0 = 1 \quad (8.7)$$

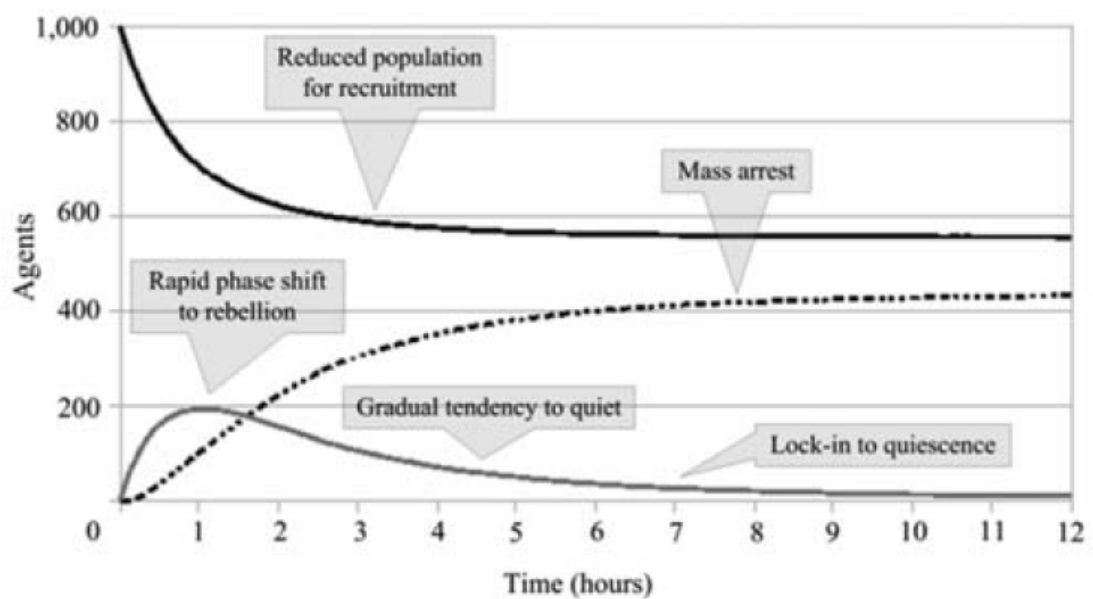
$$P_0 = 0.2 \quad (8.8)$$

$$(8.9)$$

The behaviour of the simulation shown in Figure 8.4 is similar to the behaviour of the Torrens model, shown in Figure 8.5. This model is a variation of Epstein's model of civil violence [55]. The main differences between the two models are that the Torrens model is a stochastic spatial agent-based model, and has a fixed number of police officers that can arrest nearby rioting agents. Similar to my early model agents are either rioting or are passive. If agents are arrested by the police they are jailed for a fixed time. Both figures show a rapid initial increase in the number of rioters, with a longer decreasing tail. Due to the arresting mechanism in the Torrens model, the agents that are stopped from rioting by the police flow into the jailed population rather than back into the group of passive civilians. The similarity between the two figures shows that the main dynamics of a more complex stochastic spatial agent-based model can also be captured using a set of simple deterministic differential equations.



**Figure 8.4:** Numerical simulation example for early riot model using differential equations. Numerical simulation for the passive civilians  $C$  in blue, active rioters  $R$  in yellow, and police response  $P$  in green.



**Figure 8.5:** Example of Torrens model behaviour taken from [198]. The number of rioters is shown in gray, the passive population is shown in solid black, and the jailed population is shown by the dashed black line.

## 8.5 Appendix E

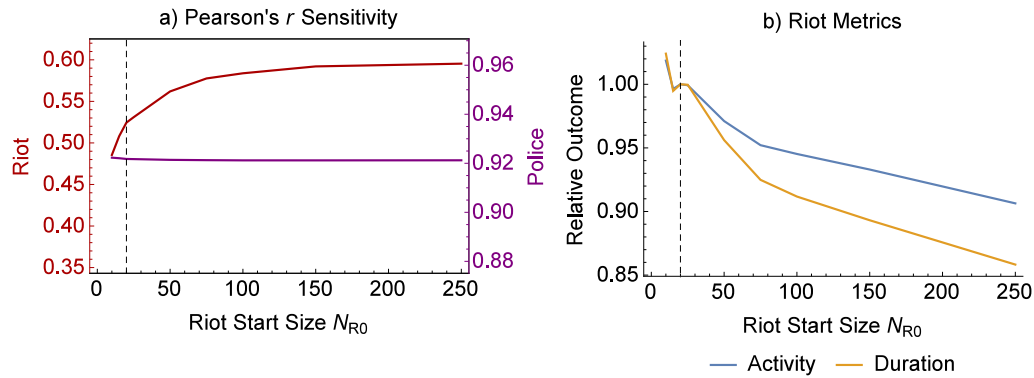
### Sensitivity Analysis

To assess the fit of the model behaviour to the data from the London 2011 riots I include a sensitivity analysis on the parameters that are not informed by data. The parameters that relate to the riot behaviour are the riot start size  $N_{R0}$ , persuasiveness  $\alpha$ , deterrence  $\delta$ , fatigue  $\varepsilon$  and the cooldown time. The parameters that influence the police behaviour are the amplitude sensitivity  $\eta$ , the baseline sensitivity  $\zeta$ , and the sensitivity increase  $\theta$ . Because a large part of the dynamics in the model are the result of the interactions between the rioters and the police, all parameters impact both the fit of the police and rioter behaviour to the data. I calculate Pearson's correlation coefficient separately for the number of rioters and the number of police officers in the model, and compare different parameter settings to the correlation coefficients obtained in the Haringey reference model run (See Figure 4.2). I compare the number of rioters to the number of incoming emergency calls to the MPS, and the number of police officers to the number of active police officers during the London riots in Haringey calculate the correlation coefficients.

#### Riot Parameters

The effect of changing the riot start size  $N_{R0}$  on the correlation coefficient is shown in Figure 8.6. Increasing the riot start size from 1 to 250 increases the correlation from 0.5 to 0.6 for the riot behaviour. The correlation between the number of police officers in the model and the data is nearly insensitive to changes in the riot start size. The limited response from both correlation coefficients to changes in the riot start size is not because of a lack of influence on riot behaviour. As shown in Figure 8.6b, the riot activity and duration decrease by as much as 15% as the riot size increases to 250 agents.

The decrease in riot activity and duration is caused by the synchronisation of agent behaviour, and an increased police response. The synchronisation of agent behaviour leads to unrealistic effect in the model, where too many agents join at the same time, and are therefore also likely to leave around the same time. Because this version of the model describes one continuous riot, the synchronised leaving of agents increases the risk that not enough participants are left to sustain riot activity. Moreover larger initial start sizes of the riot also lead to higher number of responding police



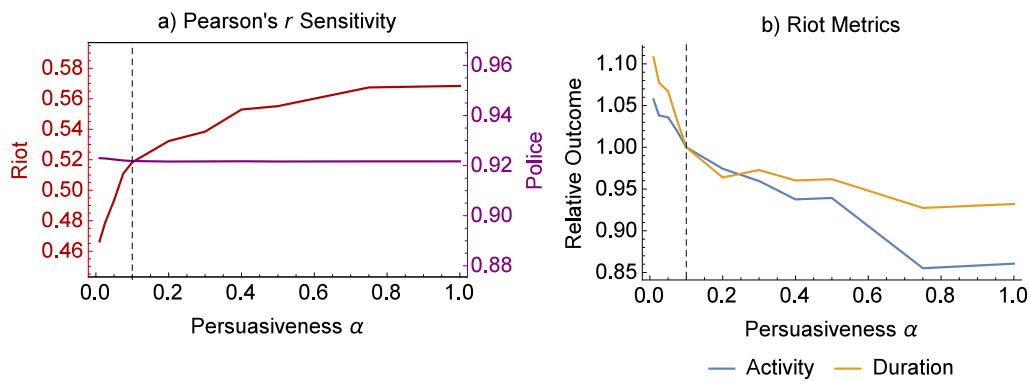
**Figure 8.6: Effect of different riot start sizes  $N_{R0}$  on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $N_{R0}$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

officers, also ending the riot earlier. The synchronisation of agent behaviour occurs as a result of multiple effects of the initial riot start size on agent behaviour. First it the higher riot start size increases the external propensity of agents to join, as there is a higher probability that they have a connection with an agent that is already in the riot. Secondly it lowers the relative repression for the initial period of the riot, as the number of responding police officers relies on the cumulative number of rioters over the whole riot and the duration of the riot, also increasing the probability that other agents will join. These combined effects make a large body of agents join within the same time period, leading to synchronised behaviour.

Figure 8.6 shows that a higher initial riot start size would perhaps give a better parameterisation of the model. The correlation coefficient for the police would remain the same, and the correlation for the number of rioters would increase. Moreover the riot duration would decrease, potentially stopping the riot activity in the model on August 10th and giving a better match to the data, instead of the 11th (See Figure 4.2. The report from the MPS however describes the start of the riot as multiple projectiles being thrown to police staff outside Tottenham police station in the evening of August 6th, followed by two police vehicles being set on fire [121], which does not match a

very large riot start size of for example, 250 rioting individuals.

Figure 8.7 shows the effect of changing the persuasiveness  $\alpha$ . Prior to the riot I simulate a pre-riot protest, where a subset of the agents come together and influence each other's grief (see Section 4.2). The persuasiveness describes the degree to which the hardship of one agent affects the hardship of other agents during the pre-riot protest.



**Figure 8.7: Effect of different parameter settings for the persuasiveness  $\alpha$  on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\alpha$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

Changing the persuasiveness has a similar effect as changing the riot start size  $N_{R0}$ . The persuasiveness has a very limited effect on the correlation of the number of active police officers, and increasing  $\alpha$  leads to higher values for  $r$ . As the agents that participate in the pre-riot protest are sampled proportional to their hardship, the average result of the pre-riot protest is a group of highly aggrieved agents. Consequently the participants of the pre-riot protest that are not in the initial group  $N_{R0}$  are likely to join quickly after the riot has started. The two parameters therefore have a similar effect, as they both influence the initial phase of the riot. The persuasiveness also has an effect at later stages of the riot, as the highly aggrieved agents are more likely to rejoin the riot after they have left, and are also less susceptible

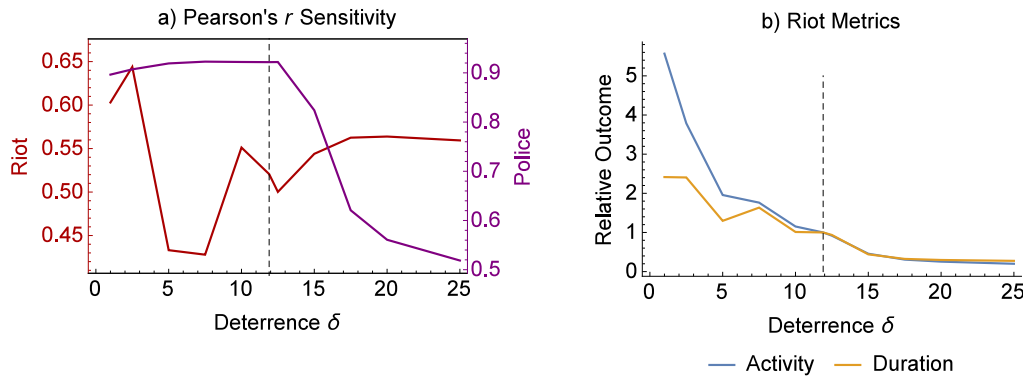
to higher values of repression caused by the growing police response.

Similarly to  $N_{R0}$ , higher values of  $\alpha$  would perhaps lead to a better fit of the model to the data, especially as there is very little influence on the correlation coefficient for the number of police officers. The persuasiveness  $\alpha$  represents the susceptibility of an agent to the hardship of other agents. An increased value for  $\alpha$  might improve correlation, but also erodes the importance of an agent's own hardship. The correct value for  $\alpha$  is therefore hard to determine, as too high values reduce the heterogeneity of the population and undermine the individuality of the agents.

The deterrence  $\delta$  influences the repression in the model, which influences both the probability that agents will join and leave the riot. An alternative interpretation of the deterrence is the equivalence of a single police officer or unit to a certain number of rioters, i.e. how many rioters a single police officer can handle, or the 'scariness' of a single police unit. The underlying idea of the deterrence parameter is that like in the London 2011 riots, the number of riot participants is often larger than the number of responding police officers, but riots can still be contained. The deterrence parameter leads to the same effect, such that a smaller number of police officers can still overcome larger riot crowds in the model. Different values of  $\delta$  impact both the correlation for the number of rioters and active police officers, as shown in Figure 8.8.

The impact of different values for  $\delta$  is larger on the correlation coefficient for the number of police officers than on the number of rioters. The police correlation first minorly increases to 0.9, and falls sharply after the deterrence increases beyond the value of the reference run to 0.5. The effect on the correlation for the number of rioters is more complex but also of a lesser degree, it first increases from 0.6 to 0.65, then decreases to 0.45, and then rises and falls again from 0.55 to 0.5, then increasing more slowly back to 0.55, after which there is a creeping decrease. A lower deterrent effect of the police leads to considerably more active and longer riots, and conversely a higher deterrence of the police leads to shorter and less intense riots.

Higher values for the deterrence lead to less riot activity, and consequently also to less police activity, therefore lowering the correlation of the number of active police officers. Lower values for the deterrence have a non-linear effect on the correlation for the number of rioters. This also leads to riot behaviour that does not match the caller data as shown in Figure 8.9. At lower values for  $\delta$ , the riots on the first day decrease too slowly, as the first episode lasts 3 to 4 days before becoming a more steady diurnal cycle for  $\delta = 1$ .

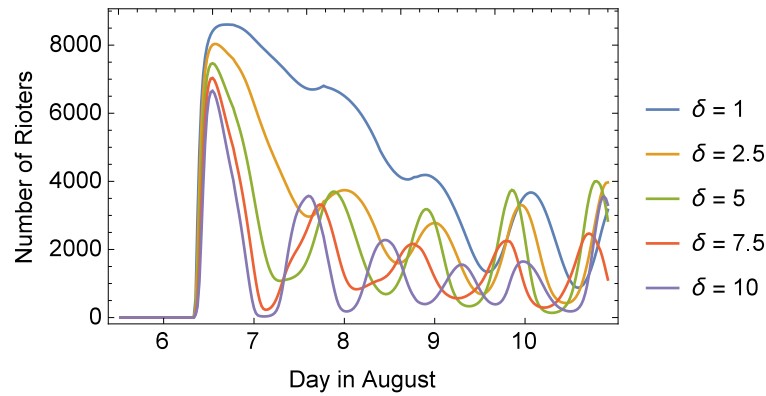


**Figure 8.8: Effect of different parameter settings for the deterrence  $\delta$  on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\delta$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

A slightly lower deterrence value of  $\delta = 10$  would have increased the correlation by 0.05, but also have increased the duration of the riot even further. The reference model run for Haringey already overshoots the riot duration of the data by one day, and a lower deterrence would increase this even further. Higher values for the deterrence lead to shorter riots in the model, but also result in considerably lower correlation coefficient for the number of police officers.

The probability that an agent will leave the riot is influenced by the repression  $R$ , and the time that an agent has spent in the riot. Whereas  $\delta$  influences the repression, the fatigue  $\varepsilon$  describes the rate at which an agent becomes tired from participating in the riot, making it more likely that an agent will leave the longer it stays.  $\varepsilon$  therefore determines the relative importance of the time that an agent has spent in the riot for the probability that the agent will leave. Figure 8.10 shows the sensitivity of the correlation coefficients and riot activity and duration to different values of the fatigue parameter  $\varepsilon$ .

Lower fatigue rates first lead to a sharp decrease in Pearson's correlation  $r$  for the



**Figure 8.9: Number of rioters in the model for different parameter values for the deterrence  $\delta$ .** The number of rioters is shown on the y-axes, the time in the model is shown on the x-axis.

number of rioters, and then sharply increase again as  $\varepsilon$  is almost 0. The correlation coefficient for the number of police officers is unaffected by lower values of  $\varepsilon$ , but decreases significantly to 0.45 as the fatigue rate increases beyond 0.17. Riot activity and duration generally decrease for higher values of  $\varepsilon$ .

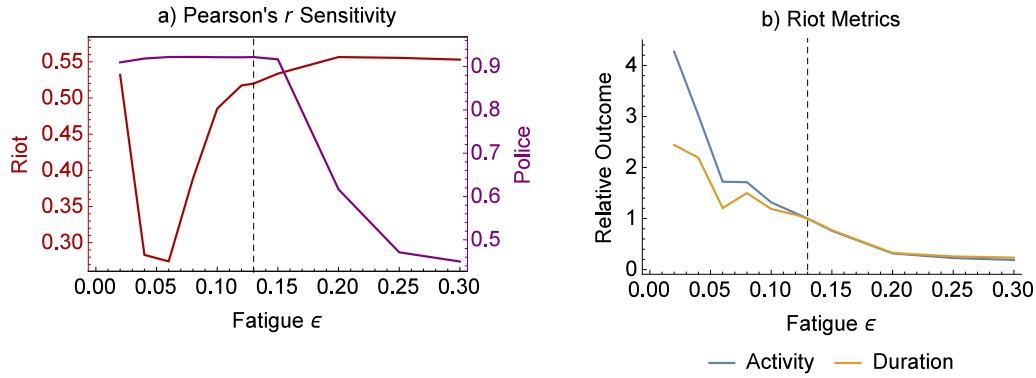
The fatigue  $\varepsilon$  impacts the period of the diurnal cycle in the model for the rioters. This explains why an increase in  $\varepsilon$  first decreases the correlation coefficient for the number of rioters, and then increases back to 0.5 as the data and the model come back into phase. Further increases have a lesser impact on the phase, explaining the relative insensitivity beyond  $\varepsilon = 0.15$ , but do make the riot considerably less active and shorter. This decrease in riot activity consequently leads to a drop in the correlation coefficient for the number of police officers.

Setting the fatigue parameter to  $\varepsilon = 0.15$  might have resulted in a better parameterisation of the model and a better match to the data. This would have resulted in a slightly higher correlation coefficient for the number of rioters, a similar correlation coefficient for the number of police officers, and a shorter riot.

After an agent leaves the riot, it cannot rejoin for a fixed period called the cooldown time. The cooldown time is measured in the number of iterations, and each iteration corresponds to 30 minutes in the real world. The effect of these inactive periods are demonstrated in Figure 8.11.

The effect of the cooldown time is similar to the effect of the fatigue  $\varepsilon$  on both correlation coefficients and the riot activity and duration. Both parameters impact





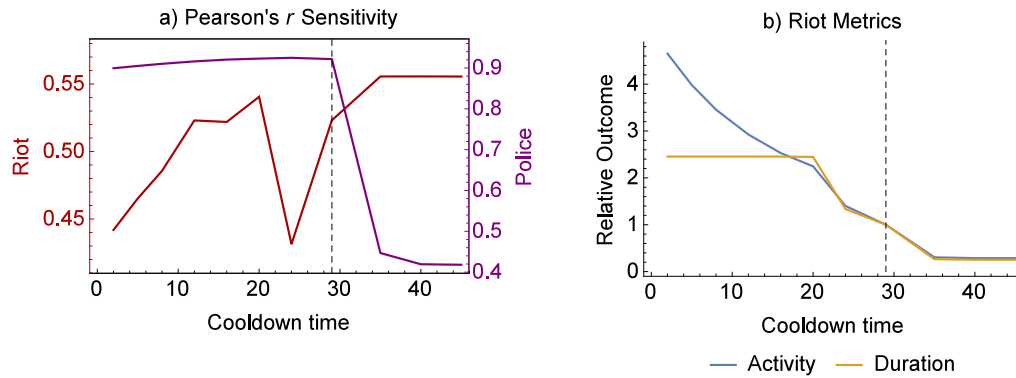
**Figure 8.10: Effect of different parameter settings for the fatigue  $\epsilon$  on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\epsilon$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

the period of the (diurnal) cycle of an agent's behaviour. Whereas  $\epsilon$  influences the time an agent will participate in the riot, the cooldown time determines how long an agent remains inactive before potentially joining again. There is a slight change in the pattern for the correlation coefficient of the number of rioters, as it first increases before reproducing the same shape as Figure 8.10.

A different cooldown value does not lead to a better fit. Longer cooldown times slightly improve the correlation for the number of rioters, but significantly lower the correlation for the number of police officers. Shorter cooldown times result in a greater mismatch between the duration of the riot in the model and the data.

### Police Parameters

The police response for the application of the model to the 2011 London riots is formulated as the absolute value of sine wave with an initial baseline (minimum value)  $B_0$  and amplitude (daily variance)  $A_0$ . The baseline and amplitude increase as a result of riot activity through  $B_R[t]$  and  $A_R[t]$ , which are added to the initial baseline and amplitude. I examine the three remaining parameters  $\eta$ ,  $\zeta$ , and  $\theta$ , that determine

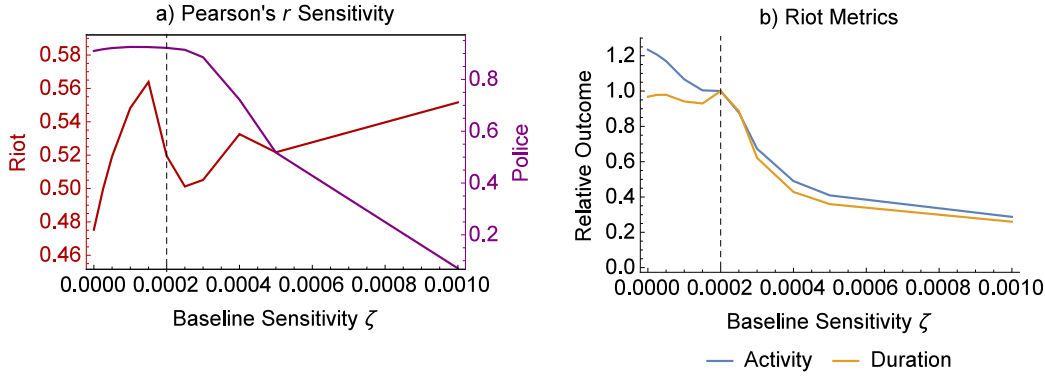


**Figure 8.11: Effect of different parameter settings for the cooldown time on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for the cooldown time on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

the sensitivities to riot activity for the amplitude and baseline increase.

Figure 8.12 shows the effect of the baseline sensitivity increase  $\zeta$ . The baseline sensitivity determines how much the minimum daily number of police officers in the model increases as a result of the past riot activity. Increases in the baseline sensitivity leads to a larger police response more quickly, and therefore results in a strong decrease in the riot activity in duration. Because the riots end earlier, the number of police officers drops more quickly compared to the data, consequently causing a significant drop in the correlation for the police behaviour of the model. The effect on the correlation for the riot behaviour is smaller and non-linear. Similar to the shape in Figures 8.10 and 8.11, the correlation first increases, then goes through a convex, and then goes through a concave upward shape, and then slowly increases.

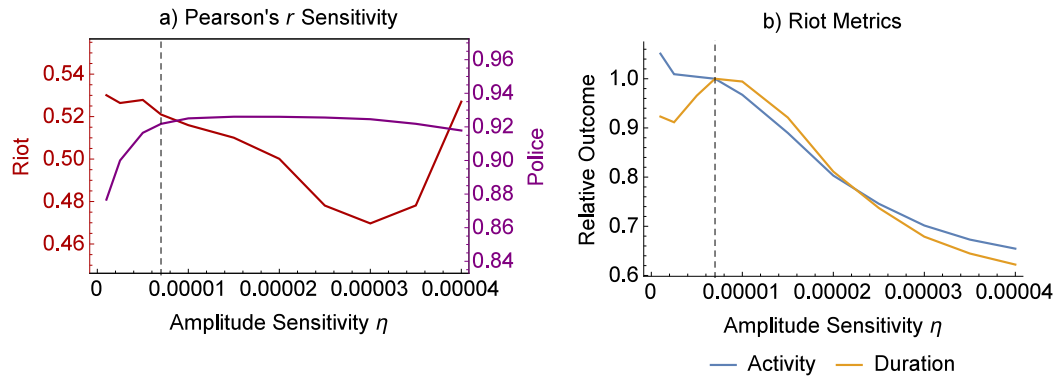
A slightly smaller value of  $\zeta = 0.00015$  could result in a better fit of the model. This would hardly influence the correlation for the police, and increase  $r$  for the rioters to 0.56, and the riot duration would slightly shorten. The riot activity would be slightly higher compared to the current parameterisation.



**Figure 8.12: Effect of different parameter settings for the baseline sensitivity  $\zeta$  time on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\zeta$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

The amplitude sensitivity  $\eta$  and time sensitivity  $\theta$  both influence the degree to which the amplitude of the police responds to the riot activity of the agents. The amplitude of the police response is determined by the sum of the initial amplitude  $A_0$  and the amplitude increase due to the riot activity  $A_R[t]$ .  $A_R[t]$  is the product of the number of rioters in the past  $R_\Sigma$ , the amplitude sensitivity  $\eta$ , and the time sensitivity function  $S[t]$ .  $S[t]$  represents the increase in effort to stop the riot specific to the duration of the riot, rather than just the intensity. The time sensitivity parameter  $\theta$  describes the degree to which the riot duration influences  $A_R[t]$ . Figure 8.13 shows the effect of different values  $\eta$ , and Figure 8.14 demonstrates the impact of  $\theta$ .

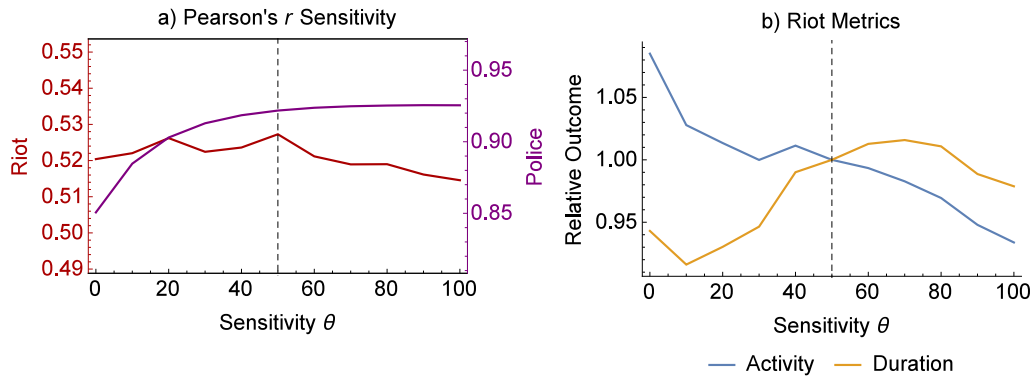
Because  $\eta$  and  $\theta$  are multiplied by each other, they have similar effects on the correlation coefficients and the riot activity and duration. The effect on the correlation coefficient for the riot behaviour is limited, as it drops steadily by a total of 0.05, and later sharply increases by the same amount for higher amplitude sensitivity values. There is a reverse effect of roughly the same magnitude on the correlation for the police, as it quickly increases by 0.04, and then is largely insensitive to further increases of  $\eta$ . The riot activity generally decreases for higher values of  $\theta$  and  $\eta$ . The duration first increases, and then decreases with higher amplitude sensitivities.



**Figure 8.13: Effect of different parameter settings for the amplitude sensitivity  $\eta$  time on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\eta$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

Other values for  $\theta$  and  $\eta$  within the plotted range would have resulted in either worse correlation coefficients or an incorrect riot duration. The similarities between the influences of  $\theta$  and  $\eta$  indicate that they could potentially be combined into a single parameter. With a reparameterisation or reformulation of  $S[t]$  it could be possible to create a new sensitivity function that is (nearly) equivalent to the current description.

The sensitivity analysis shows that some parameters, for example the deterrence  $\delta$ , could have been set differently to achieve a better fit to the data of the London 2011 riots. The suggested alternative values for these parameters would improve both the general fit, indicated by the Pearson's correlation coefficient, and shorten the riot duration, giving a better match the duration of the unrest in Haringey. In most cases the differences between the alternative and original parameter values are relatively small, and the improvements are mostly resulting in a shorter duration, rather than a big increase in the correlation coefficient. The alternative parameter values improve the fit, but do not necessarily lead to the optimal parameter settings. As I shift only a single parameter at a time, this analysis does not show the interactions between the parameter. Shifting two or more parameters at a time reveals these interactions, where

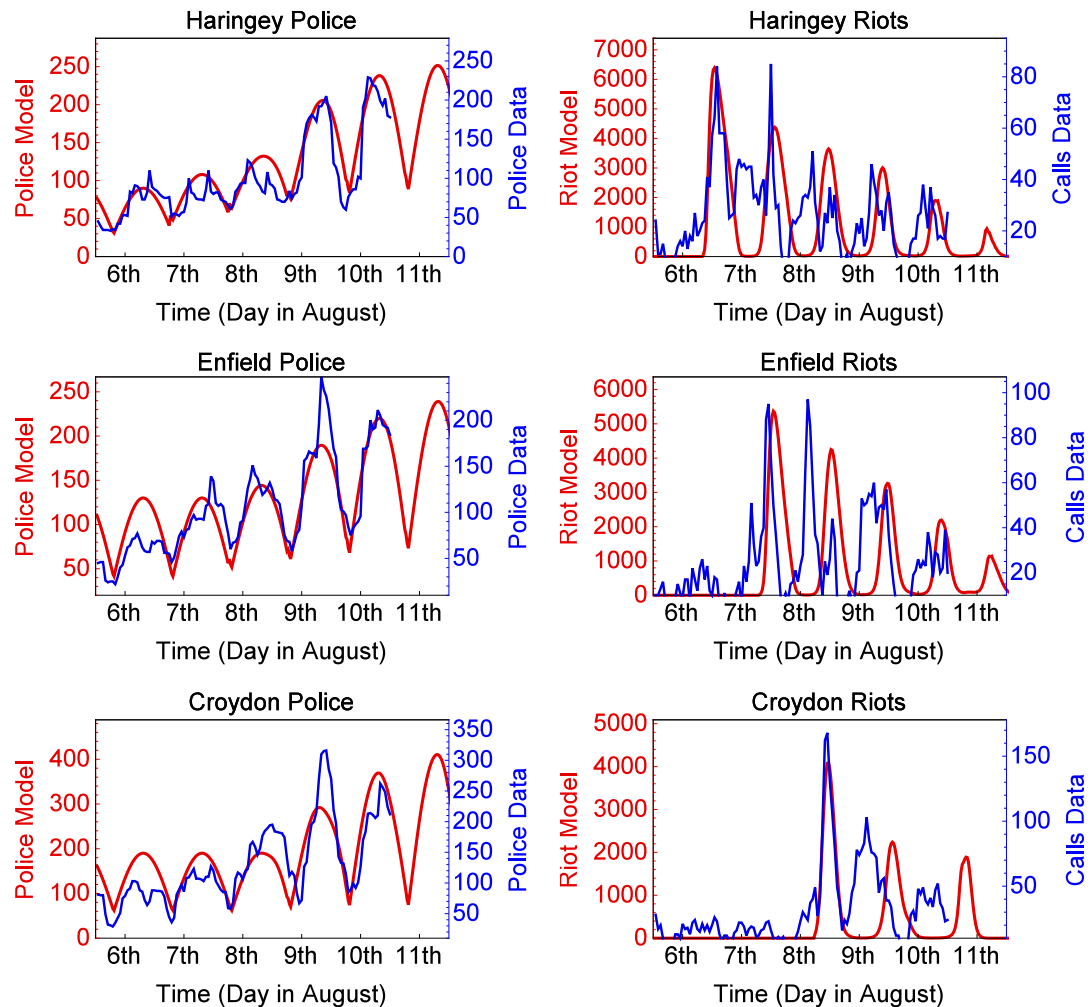


**Figure 8.14: Effect of different parameter settings for the time sensitivity  $\theta$  time on Pearson's correlation coefficient  $r$ , riot activity, and duration.** The left pane a) shows the effect of different values for  $\theta$  on Pearson's correlation coefficient  $r$  for the riot activity in red on the left and police activity in purple on the right. The correlation coefficient for the riot is calculated between the number of rioters in the model and the number of incoming emergency calls to the MPS during the 2011 London riots in Haringey [122]. The correlation coefficient for the police is calculated between the number of police officers in the model and the number of active police officers in the MPS data during the 2011 London riots in Haringey [122]. The right pane b) shows the riot activity (blue) and duration (yellow) in the model, relative to the default parameter value of the Haringey standard model run, indicated by the dashed line in both panes (See Figure 4.2)

for example the direction and strength of relationship of one parameter on the model behaviour can change as a result of different settings for other parameters (e.g. Figure 4.3).

The parameter values shown in Table 4.1 were achieved through manual model analysis. The process of this analysis is explained in Section 4.3. An alternative approach would have been to use optimisation algorithms to fit the model to the data, potentially shortening the process. For some parameters however, there are multiple values which lead to the same correlation between the data and the model. One solution that can help optimisation methods decide on equivalent results for different parameter settings, is to set constraints on the range of possible values for each parameter. Additionally some parameters have a clear non-monotonic relationship between the parameter value and the correlation. These relationships are difficult for some optimisation methods, as they can get stuck on local optima rather than iterate towards the global optimum. In order to apply an optimisation algorithm to this model, it should be able to include multiple assessments, such as the correlation coefficient and the correct riot duration. Alternatively these can be combined into a single cost function, and then be used to compute the optimum parameter values.

## 8.6 Appendix F



**Figure 8.15: Data and model behaviour for three boroughs in London 2011 riots.** *Alternative to Figure 4.2, I overlay the model behaviour and the data for the three boroughs Haringey, Enfield, and Croydon. The model behaviour is shown in red along the left y-axes, the data from the London riots is shown on the right y-axes in blue. The left column displays the number of active police officers, the right column shows the number of rioters in the model and the number of calls received by the MPS.*

## 8.7 Appendix G

### Riot Model Summary

I use an agent-based model to answer the research questions of under which conditions riots spread from one location to another, and to investigate the effects of network density, rioter placement, mixing of different potential riot groups, riot frames, hardship segregation, and demographic shifts. This appendix contains a summarised model description, explaining only the key mechanisms of the model (a more detailed explanation can be found in Chapter 3). In Chapter 5 I omit the age amplification factors that affect the hardship of agents, as the investigations are not related to a particular real-world location.

To characterize the spread of riots from one location to another, for example between cities or neighbourhoods, I describe multiple (separate) potential riot locations that are represented by coupled contained network clusters. The agents are divided over these clusters and can only join the riot at the location to which they are assigned. Starting the riot in one of these locations, I let the riot spread and calculate the probability of contagion of unrest from one location to another.

The model consists of so-called agents, that represent individuals, endowed with a decision algorithm that lets them join and leave the riot. There is also a responding police force, described as the number of police officers. The agents have an age, and a hardship  $H$  consisting of  $D$  orthogonal dimensions, described in polar coordinates by a radius between 0 and 1 and  $D - 1$  angles between 0 and  $\pi/2$  radians (rad). Each hardship dimension represents a separate issue about which agents can be aggrieved. I also describe the riot frame  $F$ , i.e. how the agents interpret the goal or cause of the riot.  $F$  is expressed along the same dimensions as  $H$ , with the imposed limit that the radius of  $F$  always remains 1. In this chapter I use two different grief dimensions, representing different independent reasons for which the agents can be aggrieved. Because the radius of  $F$  is limited to 1, the riot frame  $F$  can also be described by  $F_\phi$ , the angle between  $F$  and the x-axis (riot frame angle). The agents also have a contact network along which they share information about the riot, described after the next section.

## Age Amplification

The hardship level of each agent is convolved with an age-dependent factor that amplifies the hardship level of an agent between 15 and 29 years old and dampens hardship levels of agents outside that age band. This is similar to the idea of risk aversion used by previous studies of civil violence [55], but is based on demographic data rather than a random distribution. Past work and data has highlighted the abundance of individuals between the ages of 15 and 29 in a society as a potential indicator of civil conflict [45], and is also reflected in arrest records of the London 2011 riots [18, 164]. To implement the relationship between age and participation, I define the age-dependent factor as:

$$f(A^i) = \begin{cases} \frac{23}{60} \cdot A^i - 4.5 & 12 \leq A^i < 15 \\ 1.25 & 15 \leq A^i < 29 \\ 2.25 - \frac{A^i}{29} & 29 \leq A^i, \end{cases} \quad (8.10)$$

where  $A^i$  is the age of the agent. For numerical reasons, the radius of agent hardship is capped at one.

## Network and Communication

The contact network between agents is described as a series of interconnected clusters. These clusters represent potential riot locations for the particular agents that belong to that specific cluster. The network is generated through an adaptation of the Watts-Strogatz algorithm that creates small-world networks [211]. For each cluster the agents are placed on a ring lattice, and connected to  $k$  nearest neighbours to the right, such that the total connections is  $2k$  for each location. Then each edge is rewired to another node in all of the network with probability  $p$ . If an edge is selected for rewiring, it is rewired inside the cluster to another uniformly randomly selected node with probability  $q_{in}$ , or to a node outside the cluster with probability  $q_{out}$ . Duplicate edges or self-loops are not allowed.

Agents communicate knowledge about the riot along the contact network. If agents know about the riot they propagate the information each iteration with probability:

$$P(X = \text{communicate}) = \alpha \cdot e^{-\omega T_M}. \quad (8.11)$$

$T_M$  is the number of iterations an agent has last received information about the



riot. Agents that are in the riot are continuously updated and communicate with probability  $\alpha$  ( $T_M = 0$ ).

### Joining and Leaving Riots

The probability that an agent joins the riot is defined by three components: 1) the internal propensity or affinity  $I$ ; 2) the external propensity  $E$ ; and 3) the repression or efficacy  $R$ . The internal propensity comes from within the agents, the external propensity describes influences from outside and the repression  $R$  is a (perceived) measure of risk of participating in the riot. Only agents that know that a riot is in progress can join the riot. The final probability that an agent joins the riot is a combination of  $I$ ,  $E$ ,  $R$ , and the currency of information about the riot:

$$I = \sum_i^D H_i \cdot F_i, \quad (8.12)$$

$$E = \frac{e^{\beta \cdot C_R - \gamma}}{1 + e^{\beta \cdot C_R - \gamma}}, \quad (8.13)$$

$$R = \frac{N_R}{N_R + \delta \cdot N_P}, \quad (8.14)$$

$$P(X = \text{join}) = R \cdot \frac{I + E}{2} \cdot e^{-\omega T_M}. \quad (8.15)$$

$C_R$  is the number of connections an agent has that are in the riot,  $N_R$  and  $N_P$  are the number of active rioters and police officers.

Agents that have joined the riot can opt to leave, based on the risk of staying in the riot described by  $R$ , and the time  $T_R$  they have spent in the riot:

$$P(X = \text{leave}) = (1 - R) \cdot (1 - e^{-\varepsilon \cdot T_R}). \quad (8.16)$$

After an agent has left the riot it cannot rejoin for a given period, called the *cooldown*.

### Starting Riots

The first riot is initiated in the first riot location by manually placing  $N_{R0}$  agents in the riot, selected randomly proportional to their affinity. Every subsequent 24 hours in the model a riot can be initiated by the agents themselves at all riot locations. The process of starting a new riot is very close to the process of joining a riot. In the absence of riot

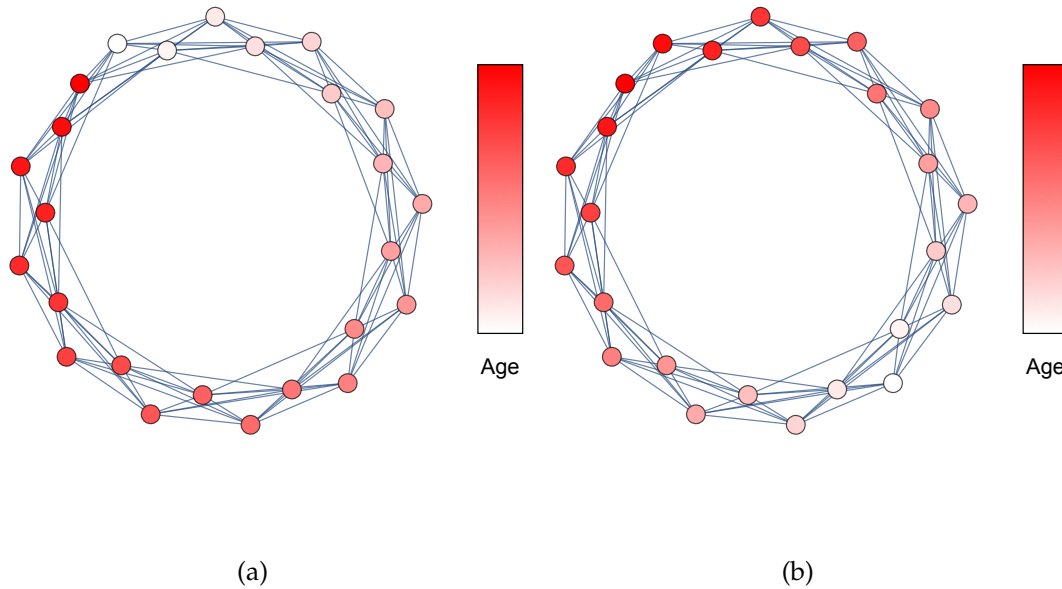
activity the agents construct an expected number of rioters  $N_R^L$ .

To calculate  $N_R^L$  all agents that knew about the previous riot, and are not on cooldown, signal whether they would join the new riot with probability  $I$  (the affinity or internal propensity). Together they form the total global number of agents that want to join  $N_R^G$ . From  $N_R^G$  the agents obtain a perceived number of agents that want to join  $N_R^L$ , that is individual to each agent.  $N_R^L$  is calculated by multiplying  $N_R^G$  with the fraction of friends of an agent that are in  $N_R^G$ . The process of selecting the agents that participate in the start of the riot is the same as joining the riot, but with  $N_R$  substituted by  $N_R^L$ .

## Police Response

The police response is represented as the number of police officers  $N_P$  at each riot location. The initial and minimum number of police officers at each location is  $P_{\min}$ , and there is also a maximum number of police officers  $P_{\max}$ . If the number of rioters increases or remains the same, or the police is outnumbered by the rioters, then the number of police officers increases by 10%. Additionally  $P_{\min}$  increases with 10 police officers for every iteration of riot activity. If the number of rioters decreases then  $N_P$  remains unchanged until the riots have stopped. Once  $N_R$  reaches zero, the number of police officers decreases by 10% until the minimum number of police officers  $P_{\min}$ . If there is no riot activity for more than 24 hours in the model, both  $P_{\min}$  and  $N_P$  decrease by 10% until the original value of  $P_{\min}$  before the start of the riots.

## 8.8 Appendix H



**Figure 8.16: Two methods of structuring information in a small-world network.** The left panel a) shows the original method of using the ring lattice to structure information in the network. Using the simplest approach to assign information, e.g. agent ages, clockwise or counter-clockwise along the ring, creates a significant difference between the first and the last nodes that are assigned. The alternative method shown on the right panel b), assigns information sequentially both clockwise and counter-clockwise, resolving this issue.

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